Mortgage Securitization and Information Frictions in General Equilibrium

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Abstract

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

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

JEL codes: D5, D82, G21, G28

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1 Introduction

Securitization has become the largest source of liquidity to mortgage originators in the United States. From 2000 to 2019, mortgage originators sold or securitized 70 percent of all residential mortgages on average during the first year of origination. However, this source of liquidity is volatile and can rapidly expand or collapse abruptly, as observed during the credit cycle of the 2000s. These volatile episodes disrupt the availability of mortgage credit to households—a key macroeconomic variable and a policymaker objective in the U.S.[1] During the last decade, extensive research has carefully documented the presence of information frictions—in the mortgage origination and securitization chain—and motivated the development of theoretical models to explain how private information can lead to abrupt declines in security trading.[2] We contribute to this endeavor by developing a theoretical and quantitative model to study the role of information frictions in accounting for aggregate mortgage credit dynamics. To what extent do information frictions amplify the impact of household shocks on mortgage credit cycles? What is the channel of transmission of shocks from the securitization market to the credit market? How do information frictions affect the design of current policies in the securitization market?

We start by presenting the main insights in a simplified credit intermediation model extended to include loan securitization. The model delivers an equilibrium connection between the securitization market and the mortgage credit market, for simplicity referred to as the credit market herein. An endogenous securitization market has the dual role of reallocating illiquid assets and providing liquidity to mortgage originators. Securitization increases the efficiency of credit funding and lowers interest rates for borrowers. However, its benefits are hindered by originators' private information about loan quality, thus leading to a classic adverse selection problem, as in Akerlof (1970). In times of high credit risk, the information friction worsens because originators' incentives to sell low-quality loans and retain high-quality ones lead to a deterioration in the return of securities. This deterioration fur-

[1] The U.S. government, through the government-sponsored enterprises Freddie Mac and Fannie Mae, has the explicit objective of supporting stable and liquid funding of mortgage credit to households.

[2] Adelino et al. (2019), Piskorski et al. (2015a), Keys et al. (2010), and Downing et al. (2008) are among the seminal contributions documenting that sellers of loans are better informed than prospective buyers about a loan's quality. Furthermore, sellers actively take advantage of such information asymmetry, giving rise to adverse selection in secondary markets. On theoretical grounds, building on the insights of Akerlof (1970), the economics profession has developed models of dynamic adverse selection (see Guerrieri and Shimer (2014), Kurlat (2013), Chari et al. (2014), and more recently Caramp (2019)), which have furthered our understanding of how information frictions can lead to declines and collapses in security trading.

ther leads to sharp declines in security issuance and mortgage credit to households. Hence, information frictions generates a multiplier effect of households' shocks in the mortgage market's aggregates. A quantification of this information frictions multiplier during the Great Financial Crisis (GFC) shows that it could have amplified the mortgage credit contraction by a factor ranging between 1.2 to 1.3. The model accounts for large fluctuations in the mortgage market aggregates arising from households income and housing shocks. Two important factors are at play: (i) the severity of information frictions, which amplifies fluctuations in prices in response to household shocks, and (ii) the cross-sectional characteristics of the U.S. mortgage market, which highlight the importance of the securitization liquidity channel for credit provision.

Our dynamic stochastic general equilibrium model builds on the standard setup of financial intermediation used in the macro literature of housing. An impatient borrower household takes on long-term mortgages to finance purchases of housing services and non-durable goods. As in practice, they are exposed to aggregate income risk, housing risk, and prepayment risk. The supply side of the credit market comprises a large number of lenders operating with private equity. Motivated by the specific features of the U.S. mortgage market, we extend this standard setup along several key dimensions. First, the borrower household can endogenously default on mortgage loans, which defines the quality of loans that lenders hold. Second, lenders face heterogeneous loan origination costs, which capture the differences in loan origination technologies and lending opportunities among mortgage originators. Third, as in practice, lenders face liquidity and information frictions. They are financially constrained by having limited access to debt markets, and they can privately identify the quality of the mortgages in their portfolios. Fourth, there is a securitization market where lenders can sell loans—to obtain liquid funds—and buy securities.

The securitization process relies on pooling loans of heterogeneous qualities to form securities. We model a securitization structure that resembles essential features of the to-be-announced (TBA) forward market, the largest liquid market for mortgage-backed securities (MBS) in the U.S. On the theory side, our setup combines elements from a model of asset creation and reallocation—affected by information asymmetries about asset qualities—to model the securitization liquidity channel of mortgage credit.[3] Hence, we further the theory

[3] In the TBA market, there is no tranching or structuring of cash flows. Instead, the underlying cash flows are collected by a pass-through structure and forwarded to security holders. All securities trade at a pooling market price. We focus on replicating such a market structure. The other type of MBS trading is known as "specified pool" trading, where securities of different qualities trade at different prices. See Section **??** for details.

by connecting the dynamics of the securitization market to those of the credit market. Two novel contributions arise. The first is joint price determination, meaning that the price of mortgage loans and the price of securities are jointly determined in equilibrium. The second is that the severity of information frictions becomes an endogenous function of market prices, household's default rates, and lenders' trading decisions.

The government's involvement in the securitization market is captured by a credit guarantee that compensates buyers of securities for the losses associated with household default. The government finances this policy by imposing a distortionary tax on mortgage originators and lump-sum taxes on households. The aim of the policy is to encourage a stable demand for securities, thereby increasing the volume of security issuance and the volume of credit that is intermediated to households. In this sense, the policy resembles the role of the credit guarantees provided by government-sponsored entities (GSEs) to buyers of MBS.[4]

The model delivers boom-bust credit cycles driven by household credit risk with a novel feedback mechanism between the credit and the securitization markets. Episodes of high (housing or income) risk can lead to a surge in mortgage defaults, which then affects the composition of high- and low-quality loans in lenders' portfolios. For lenders, differences in origination costs and limited liquid funds generate motives for securitization trading. When trading, lenders split into three groups: securitization sellers, securitization buyers, and holders. Private information about a loan's quality gives rise to adverse selection in security trading. Sellers have incentives to sell low-quality loans and selectively retain high-quality ones when the market price is lower than their valuation. Buyers understand that these incentives are in place; when buying securities, they expect that a fraction of the securitized loans will fail to perform due to household default. Hence, information frictions about loan quality raise the effective cost of trading. In times of low credit risk, the liquidity value and the cost-sharing benefits of securitization generally exceed the costs of information frictions. As households' credit risk rises, information frictions become more pronounced. Consequently, security buyers expect a higher fraction of securitized loans not to perform, the demand for securities falls, and securities trade at lower prices. In the credit market, loan sellers face an endogenous liquidity shortage derived from the unwillingness to securitize their portfolios at lower market prices. Given the limited access to debt markets, a contraction in the credit supplied to households ensues. This contraction further deteriorates households' balance sheets, leading to an amplification loop that prolongs contractionary credit cycles.[5]

[4]In practice, the GSEs buy mortgages from originators, pack them into mortgage-backed securities, and insure MBS buyers against the default risk from borrower households.

[5]A collapse in the securitization market can endogenously occur in equilibrium when information frictions

Our calibrated benchmark model matches key moments of the cross section and the time series of main mortgage market aggregates. A quantitative test of the model shows that it can successfully replicate the dynamics observed during the GFC. In the data, aggregate mortgage credit contracted by 40 percent and aggregate MBS issuance contracted by 30 percent on average from 2008 to 2013. When households in the benchmark economy are hit by the same sequence of income and housing valuation shocks observed in the data during this period, the model replicates two-thirds of the contraction in mortgage credit and the full contraction in MBS issuance. A comparable economy without information frictions cannot replicate the same degree of amplification for an identical sequence of shocks. Consequently, we can estimate the information frictions multiplier on various mortgage market aggregates. Notably, the magnitude of the multiplier is a function of the lenders' ability to identify a loan's quality privately and of the distribution of origination costs. The latter object informs the model about the gains from securitization trading and the reliance on its liquidity for mortgage lending.[6] on average, one-fifth of the model's predicted decline in mortgage lending arises from the amplification effect of information frictions on household shocks, while housing and income shocks account for the rest. This observation contributes to understanding the factors at play during the GFC; showing how households mortgage risk dynamics, together with agency problems that map into liquidity and information frictions, can account for credit dynamics at the aggregate level.

On policy grounds, we find that pricing credit guarantees in a manner that accounts for the amplification factor of information frictions may enhance the financial stability of the system—reducing the volatility of prices and quantities and the probability of a market collapse. Our analysis indicates that although the increase in the price of credit guarantees generated higher revenues in the post-GFC economy, the policy still generates a substantial deficit, suggesting that credit guarantees are still underpriced. Our estimate of the break-even price for credit guarantees is higher than the one currently charged by GSEs, and implementing it can generate welfare gains for borrowers and lenders by lowering equilibrium mortgage default, housing equity losses, and tax payments. We further discuss the drawbacks

become too severe. In such episodes, the credit market still operates. However, lenders face higher intermediation costs and have less liquid funds, which leads to a higher mortgage rate, lower credit intermediation, and lower aggregate consumption of housing and final goods.

[6] We estimate this distribution by matching the cross-sectional moments of the model's lending distribution to its data counterpart using originators' lendging volumes from the Home Mortgage Disclosure Act (HMDA) database. Based on this, contractions in security issuance generate large contractions in the volume of credit when large originators—that depend on securitization for credit funding—switch from securitizing their entire portfolio to securitizing a small fraction.

of credit guarantees as a stabilization instrument in its current state.

Layout. The rest of this introduction briefs on the related literature. Section **??** presents relevant features of the mortgage market that motivate the model in Section 3. Sections **??** and 4 present the theoretical and quantitative analyses, respectively, and Section 5 concludes.

Related Literature. This paper fits within the strand of literature that introduces financial frictions into dynamic stochastic general equilibrium (DSGE) models of housing (Iacoviello (2005); Justiniano et al. (2015); Landvoigt (2016); Elenev et al. (2016); Justiniano et al. (2019)). We contribute to this literature by showing that information frictions—coupled with liquidity frictions in credit markets—can amplify credit cycles. Applying our framework to the GFC indicates that information frictions may have played an important role in amplifying the observed mortgage credit contraction. Along this line, Justiniano et al. (2015, 2019) argue that credit supply forces—such as lending constraints that restrict a lender's available funds for mortgage credit—are quantitatively more important than credit demand forces in explaining fluctuations in mortgage debt and the housing market, as documented by Mian and Sufi (2009).[7] Our model provides a microfoundation for Justiniano et al. (2019)'s lending constraints by introducing securitization as a major source of liquidity that relaxes mortgage lenders constraints. Landvoigt (2016) also introduces securitization in a DSGE model although in a reduced form. Our approach goes one step further by modeling an endogenous securitization market where lenders trade off liquidity benefits against information frictions costs. This approach is consistent with the development of securitization as an important source of funding for mortgage credit in the U.S. since the 2000s.[8]

Information frictions are motivated by a vast body of literature that documents the presence and relevance of private information along the mortgage issuance and securitization chain. Downing et al. (2008), Keys et al. (2010), Elul (2011), and Adelino et al. (2019) consistently find that mortgage originators retain mortgages that are, on average, of better quality than mortgages sold and securitized in the agency and non-agency MBS segments, thereby generating an adverse selection problem.[9] Shimer (2014) performs a comprehensive

[7]On the credit demand side, although there is no doubt that house price expectations played an essential role both in the build-up and in the bust of the housing market (Kaplan et al. (2020)), the abrupt collapse of securitization and the strong contraction in mortgage lending speak primarily to a liquidity event.

[8]Securitization has several advantages as a technology to enhance financial intermediation as it is associated with: i) a lower cost of capital; ii) the creation of high-quality safe assets by pooling risk, lowering bankruptcy, and lowering tax-related costs; and iii) gains from financial specialization (see Gorton and Metrick (2013) for an in-depth analysis).

[9]Keys et al. (2010) find evidence that when mortgage originators expect to retain rather than sell a loan, they screen it more carefully. In the non-agency segment, Elul (2011) finds that the rate of delinquency

review of the studies measuring private information in the MBS market along several dimensions and how the market deals with it. On theoretical grounds, we build on extensive work that studies adverse selection in financial markets, a tradition that dates back to Akerlof (1970). Our choice of modeling adverse selection in asset markets applies and extends well known frameworks of asset creation and reallocation under private information (Kurlat (2013); Chari et al. (2014); Bigio (2015)) to capture specific features of the TBA forward market for MBS. It also shares elements present in Vanasco (2017), Caramp (2019), and Asriyan (2020). These papers show that adverse selection can generate large fluctuations in the volume of traded assets by amplifying the effects of exogenous shocks in the economy.[10] The model contributes to this literature by showing how information frictions can not only lead to the collapse of the securitization market but also spill over into the credit market and subsequently exacerbate borrowers' financial conditions, forming a feedback loop that amplifies credit cycles.

To our knowledge, our research is the first to quantify the aggregate effects of information frictions in the mortgage market through a securitization liquidity channel. Along this line, our results are consistent with the empirical findings of Calem et al. (2013), which measures the impact of mortgage lending derived from the liquidity shock that commercial banks faced during the collapse of the private-label MBS market. They find that commercial banks highly dependent on securitization contracted mortgage credit six times more than similar banks that did not participate in securitization. Other work quantifies information frictions in corporate lending markets; Crawford et al. (2018), and Darmouni (2020).[11] While these works focus on the relationship between corporate borrowers and lenders, our paper focuses on the information frictions between lenders and investors and shows that the aggregate effects on lending markets can be sizeable in general equilibrium.

This paper also contributes to the literature that studies the effects of government policies on the mortgage and housing markets. Elenev et al. (2016) develop a general equilibrium

for a typical prime loan is 20 percent higher if it is privately securitized. Similarly, Adelino et al. (2019) document that mortgage originators consistently retained the better-performing loans and sold those with poorer performance first in the years previous to the GFC. Downing et al. (2008) finds similar results in the agency segment.

[10] Other models of adverse selection consistent with this feature are those developed by Chari et al. (2014), which incorporate reputation concerns, and Guerrieri and Shimer (2014); both works relax the assumption of non-exclusive markets.

[11] Crawford et al. (2018) do so by estimating a structural model of credit demand that focuses on the interaction between market power and asymmetric information. Darmouni (2020) estimates the magnitude of information frictions limiting credit reallocation to firms during the 2007–2009 financial crisis.

model of the mortgage market. They find that underpriced mortgage guarantees, together with deposit insurance, encourage the banking sector to lever up excessively. We provide a complementary view of the effects of a mortgage guarantee policy. By modeling information frictions, our framework generates a meaningful role for a guarantee policy in the securitization market. A credit guarantee helps stabilizing the demand for securities and the flow of liquidity to mortgage lenders. Similar to Elenev et al. (2016), although for a different mechanism, we also find that credit guarantees were underpriced before the GFC.

2 A Stylized Model

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

Environment. Consider an economy populated by a continuum of lenders of mass one operating in two periods: $t = 0, 1$. In the first period, lenders use their resources to originate loans, and in the second, they consume all their accumulated wealth. At the beginning of time 0, each lender j observes her cost z^j of originating new loans n^j. This idiosyncratic origination cost distributes iid across lenders with cumulative distribution function $F(z)$ in the support $[\underline{z}, \bar{z}]$. We interpret z as embedding aspects of heterogeneity in mortgage underwriting, screening, and lending opportunities for a wide variety of mortgage originators.[12] Each lender starts with a cash endowment $w > 0$ and a legacy portfolio of loans $b_0^j > 0$ due in period 1. A lender's budget at time 0 is $z^j n^j q = w$, where $q > 0$ represents the discounted price of new loans, which all lenders take as given as they are assumed to operate in a perfectly competitive credit market. Legacy assets b_0^j represent previous loans extended to unmodeled borrowers and are subject to aggregate default risk: a fraction $\lambda \in (0, 1)$ of them defaults and pays nothing at $t = 1$. We assume that lenders hold a diversified legacy portfolio similarly exposed to the default risk; hence, default effectively splits a lender's portfolio into a performing and non-performing fraction. The performing legacy plus the newly originated loans accumulate into the next period so that the individual law of motion of legacy assets

[12] Our approach aligns with the conventional way of modeling heterogeneity among financial intermediaries in the literature; it is analogous to Kiyotaki and Moore (2005); Kurlat (2013) random arrival of investment opportunities and produces similar qualitative outcomes to introducing heterogeneous intermediation costs proportional to loan returns as in Boissay et al. (2016).

is $b_1^j = (1-\lambda)b_0^j + n^j$. To keep the model simple, we abstract from modeling borrowers and instead, assume that the aggregate demand for new loans is given by $N^D(q) = \Theta q^{\frac{1}{\epsilon}}$, where $\Theta > 0$ is a demand shift parameter, $\epsilon > 0$ governs the elasticity of credit demand.

Lending without securitization. In this environment, origination through z is the only technology available to lenders to transfer resources to the next period. Maximizing consumption is equivalent to maximizing the size of the next period's portfolio, given that in period 1, lenders consume all their accumulated wealth. 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. Characterizing this problem is trivial. Each lender invests all her resources in operating her lending technology and originates $n^j = \frac{w}{z^j q}$ given their z^j cost. Aggregate credit supply is given by $N^S(q) = \int_{\underline{z}}^{\bar{z}} \frac{w}{zq}\, \mathrm{d}F(z)$, notice that aggregate credit supply is limited by the liquid funds available to lenders given by their cash endowment.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

where credit demand $N^D(q)$ is given by the same function specified before. The system (4)-(5) reflects the equilibrium connection between the securitization and credit markets. By explicitly modeling such a connection, our model shows how allocative efficiency gains from securitization lead to an increase in aggregate credit supply and to a reduction of credit intermediation costs— since in equilibrium, only the lowest-cost lenders originate new loans —which implies a more favorable price of credit for borrowers than in the absence of securitization.[13] This intuition is formalized below in Proposition 1.

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

Securitization with private information. We now introduce information asymmetries among lenders by assuming that, at the beginning of period $t = 0$, each lender can privately predict and identify within their legacy portfolio the fraction of loans that will non-perform. The information asymmetry disappears by the end of the period, and the holders of non-performing loans recover nothing.[14] The securitization market operates as before: lenders may sell legacy loans or buy securities at a pooling price $p > 0$. However, because of private information, lenders can now sell loans selectively; let s_H represent sales of loans a lender identifies as of high-quality— those that will likely perform, and s_L for low-quality loans—

[13] 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.

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

those loans that will likely non-perform. At $t = 0$, the budget set of lender j is:

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

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

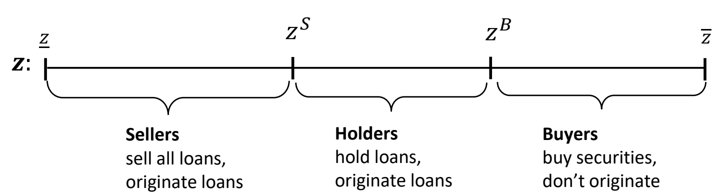
$$\mu(p, q) = \frac{S_L}{S(p, q)}, \tag{7}$$

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

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

The characterization of lenders trading decisions $\{n, d, s_H, s_L\}$ is similar to the previous setup. The main difference is that lenders may now sell loans selectively due to private information. At any $p > 0$, all lenders have incentives to sell all their low-quality loans first, choosing $s_L^j = \lambda b_0^j \quad \forall j$. In equilibrium, the rest of decisions are characterized according to cutoffs $\{z^S,\ z^B\} \equiv \left\{\frac{p}{q},\ \frac{p/q}{1-\mu(p,q)}\right\}$ that split lenders into three groups according to their cost $z \in [\underline{z}, \bar{z}]$, as shown in Figure 1. 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.

Figure 1: lenders' trading groups with private information



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

Kurlat (2013) shows that, due to adverse selection, the securities market may collapse or become inactive whenever the traded fraction of low-quality assets is too high.[15] On the other hand, an inactive securitization market implies that there is no positive price that clears supply and demand. In such a scenario, the credit market still operates but the aggregate supply of credit will be given by integrating lending decisions across all lenders that originate new loans using their origination technology, as we did in the model without access to securitization. Hence, since the securitization market can be active or inactive, credit supply becomes contingent on its trading equilibrium outcome. Proposition 2 summarizes this insight. As before, we can derive analytical expressions for trading policy functions and the aggregates in each market, see Appendix G for details. Equilibrium prices (p, q) are obtained by solving the joint system of equations given the clearing conditions of the credit and the securitization markets, similar to the system (5)-(4).

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

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

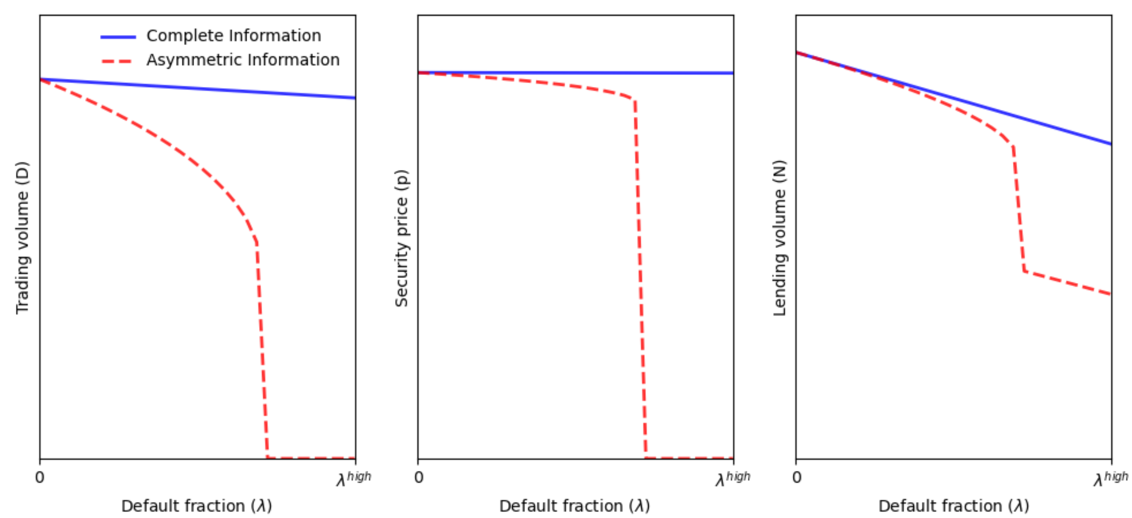
where $z^B = \frac{p/q}{1-\mu(p,q)}$ *is the equilibrium cut-off that defines the marginal lender-seller in an active securitization market.*

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

Comparative Statics. An important property of the model is that the information wedge endogenously widens as the default rate (λ) increases. Figure 2 compares the response of market aggregates between an economy with information frictions against an economy with complete information; it shows that the contraction of aggregate credit to changes in the default rate is amplified in the presence of information frictions.

Figure 2 shows how information frictions may amplify the response of aggregates to changes in default risk; the left panel shows that as the fraction of defaulting loans in the economy increases, the volume of securities traded declines much more rapidly in the economy with information asymmetries. Security prices follow a similar pattern: high default risk results in a higher proportion of securitized low-quality loans, driving up the cost of purchasing securities and reducing demand. As a result, the price of securities that clears the market falls. Absent information frictions, low-quality loans are not traded, and the price of securities remains unaffected by default risk (central panel). The discontinuity observed in trading volume and security prices represents the threshold of default risk above which the securitization market becomes inactive. Due to the equilibrium connection between both markets, a lower securitization volume implies lower liquidity available for new lending in the credit market. Moreover, a shutdown of securitization may induce strong non-linear dynamics in lending volumes, amplifying the contraction of credit (right panel).

Figure 2: Amplification of aggregates to credit default



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

Up to this point, we have illustrated how information frictions in securitization can amplify the response of credit aggregates when default risk is high. In the quantitative section 4, we show that (i) in general equilibrium, a "financial accelerator" effect in the credit market arises once borrower's default is endogenously modelled[16]; (ii) the data on cross-sectional moments of mortgage lending is informative about the magnitude of the amplification of information frictions.

3 The Quantitative Model

This section lays down the full quantitative model we take to the data. Time is discrete and infinite. There are three types of agents: a continuum of lenders of mass one, a borrower household, and a government. Borrowers discount time (β^B) at a higher rate than lenders (β^L): $\beta^B < \beta^L$.

3.1 Lenders

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

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

Lenders are assumed to have limited access to debt markets and to operate only with private equity given by their ownership of the household's debt. A lender j's stock of mortgage loans is denoted by b_t^j. We assume that each lender holds a diversified loan portfolio across household members such that each is equally exposed to household prepayment η_t and default $\lambda(\bar{\omega}_t)$ risks. The funding sources for a lender are the mortgage payments on her stock of loans, the foreclosure cash inflows from non-performing loans, and the cash receipts from sales of loans in the securitization market—to be explained below. Our setting focuses on capturing relevant features of the financial institutions—banks and non-banks—operating in the U.S. mortgage market, i.e., that a large fraction of mortgage originators have limited funding sources and act as financially constrained intermediaries facing credit and prepayment risks from household's mortgages.

Private Information. At the beginning of the period, every lender privately identifies the mortgages with low and high repayment prospects in her current stock; we label $x_{\ell t} \in [0, 1]$

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

the fraction of low-quality mortgages (i.e., mortgages with low repayment prospects) and $1 - x_{\ell t}$ the fraction of high-quality mortgages. The essential distinction is that a low-quality mortgage may enter foreclosure with probability ρ and repay with probability $1 - \rho$. For simplicity, it is assumed that high-quality mortgages repay with certainty. 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 $m_{\ell t} = (1-\rho)m_t + \rho\Psi(\bar{\omega}_t)$, while high-quality mortgages pay $m_{ht} = m_t$. In equilibrium, the aggregate expected foreclosure rate equals the aggregate default rate:

$$\rho x_{\ell t} = \lambda(\bar{\omega}_t) \qquad \forall t. \tag{10}$$

The source of private information arises from a lender's capacity to privately identify a mortgage's quality at the beginning of each period, and it captures the observation that ex-ante, a lender can better predict and identify high- and low-quality loans within her portfolio but does not know with certainty which loans will default. An outsider cannot make such a distinction. Notably, at the time of sale, all mortgages, high and low-quality, are in good outstanding. By the end of the period, once the household's default rate is determined in equilibrium, all mortgages, performing and non-performing, are publicly identifiable. Private information about a loan's quality that leads to information asymmetries between mortgage originators and investors often—although not exclusively—arises during the borrower's screening stage.[17] For instance, originators may have *soft information* about a borrower's credit quality, often retained to their advantage. Or originators may observe borrowers misreporting on loan applications or actively misrepresenting their profiles, which carries over to MBS buyers.[18] We abstract from modeling the specific sources of these information asymmetries and instead take them as part of the environment.

Loan Origination Technology. We assume that lenders are heterogeneous in their lending technology. At the beginning of each period t, a lender draws a loan origination cost z_t^j, which

[17] We abstract from modeling information asymmetries between borrowers and lenders (Keys et al. (2010)). Borrowers' credit risk screening is relevant to understanding moral hazard incentives on the side of the originator, see Vanasco (2017); Neuhann (2019); Caramp (2019).

[18] Soft information is referred to as *soft* because it is difficult to quantify—for instance, the originator's expectation about a borrower's income stability–as opposed to hard information, which is usually reflected in quantitative borrowers' profiles (e.g., LTV, income, credit scores). Evidence of these information asymmetries is compelling; see Keys et al. (2010) and Demiroglu and James (2012). Misrepresentation of borrowers' profiles is an important determinant of their default risk (see Jiang et al. (2014) and Piskorski et al. (2015b)). Asymmetries of information can arise even if both parties observe the same information. For example, originators developing superior valuation models relative to MBS buyers can give rise to such asymmetries (see Shimer (2014) and Krainer and Laderman (2014)).

is independent and identically distributed across lenders and time and follows a continuous cumulative distribution function $F(z)$ in the bounded support $[\underline{z}, \bar{z}]$. The loan origination technology is linear, and each lender j originates new loans of size n_t^j at a gross cost of $n_t^j z_t^j$.[19] This stochastic cost represents a source of idiosyncratic risk for each lender, and it is assumed to remain private for the period so that other lenders cannot use this information to infer trading decisions in the securitization market. The economic interpretation is that z_t^j embeds aspects of heterogeneity in mortgage underwriting, screening, and servicing costs and lending opportunities of a wide variety of mortgage originators.[20]

Securitization Market. Lenders have access to a securitization market where they can buy securities and sell their stock of loans in inventory b_t^j. A lender j makes trading decisions $\{s_{ht}^j, s_{\ell t}^j, d_t^j\}$ where s_{ht}^j represents sales of high-quality loans, $s_{\ell t}^j$ represents sales of low-quality loans, and d_t^j represents purchases of securities. As in practice, the securitization process consists of pooling loans of heterogeneous qualities to form securities. A mortgage-backed security is a representative bundle of all loans traded, featuring the same coupon payment and maturity structure as the loans that make up the security bundle.

We assume that trades in the securitization market are non-exclusive and anonymous. This assumption guarantees that all loans and securities trade at a pooling price p_t—endogenously determined in equilibrium.[21] In this environment, private information implies that only the total volume of a lender's loan sales is observable $s_{ht}^j + s_{\ell t}^j$, and it is not possible to distinguish sales for liquidity needs from sales for strategic motives. A classic adverse selection problem, as in Akerlof (1970), naturally arises—since buyers are well aware of sellers' incentives to sell low-quality loans first. Let μ_t represent the fraction of securitized loans that enters foreclosure:

$$\mu_t = \frac{\rho S_{\ell t}}{S_t}, \tag{11}$$

[19] Our approach aligns with the conventional way of modeling heterogeneity among financial intermediaries in the literature. It produces similar qualitative outcomes to introducing heterogeneous intermediation costs proportional to loan returns as in Boissay et al. (2016), or to heterogeneous returns to investment as in Kurlat (2013).

[20] The assumption of random types drawn every period rules out potential reputation concerns in the securitization market—this is equivalent to assuming one-period living banks as in Boissay et al. (2016). We interpret a lender's random types as reflecting the arrival of lending opportunities in the form of intermediation costs, which is analogous to Kiyotaki and Moore (2005) random arrival of investment opportunities.

[21] These assumptions are a tractable way of ensuring that adverse selection persists over time in our environment. Chari et al. (2014) show that the adverse selection problem persists over time and leads to pooling equilibria even when these assumptions are relaxed—that is, they model lenders that are not anonymous and whose types are persistent over time.

where $S_{\ell t}$ is the aggregate supply of low-quality loans, S_{ht} denotes the aggregate supply of high-quality loans, and $S_t = S_{ht} + S_{\ell t}$ the aggregate supply of all loans traded. Private information about a mortgage's quality also changes the expected cash flow of MBSs for security buyers; instead of receiving the average mortgage payment at maturity, they receive $m_{dt} = (1 - \mu_t)m_{ht} + \mu_t \Psi(\bar{\omega}_t)$, which acknowledges that fraction μ of all traded mortgages is liquidated due to borrower's default.

A discussion of modeling choices is appropriate. Although there are other forms of securitization, we aim to represent the main features of the largest liquid market for MBS in the U.S. (see section **??**). In this respect, our setting captures the pooling aspect of the TBA forward market, the incentives to deliver low-quality loans first, and the role of government credit guarantees in shielding investors from borrowers' credit risk—introduced below.[22] From a theoretical perspective, our design of the securitization process combines elements from models of asset creation and reallocation—as in Kurlat (2013); Chari et al. (2014); Bigio (2015)—with relevant features of the mortgage market to build an internally consistent model of credit finance. Two aspects set our model apart. The first is joint price determination, meaning that the prices of credit and securities $\{p_t, q_t\}$ are jointly determined in equilibrium. The second is endogenous liquidity determination, meaning that securitization liquidity is a function of market prices, the household's default rate, and the severity of information frictions.

Government policy. In the agency securitization market, the GSEs guarantee MBSs against the default risk of the underlying mortgages and finance this insurance by charging a fee to the mortgage originator, known as the guarantee fee. We model two aspects of the MBS guarantees provided by the government policy; the first is that the promised cash flow of an insured MBS, m_{gt}, equals the cash flow of high-quality mortgages: $m_{gt} = m_{dt} + \mu(m_t - \Psi_t(\bar{\omega}_t)) \equiv m_{ht}$, which effectively shields a security buyer from the borrower's default risk leaving her exposed to the borrower's prepayment risk only. The second aspect is a subsidy to the price of an MBS denoted by $\tau_t(\mu_t)$, which captures government price incentives provided to MBS buyers to ensure liquidity in the securitization market; we make

[22] A TBA trade has three main attributes. First, a buyer learns the exact characteristics of the securities just before delivery rather than at the time of the trade. This means sellers choose which loans will be delivered to buyers at settlement after some information about the loans' quality has been realized. Second, buyers understand that sellers have incentives to sell the lowest-value assets that satisfy the terms of trade. This arrangement gives a seller an advantage to better predict the quality of a loan. And third, securities feature a credit guarantee that protects investors against credit losses deriving from mortgage defaults. Details about TBA trading are outlined in the *Good Delivery Guidelines* developed by SIFMA; see Vickery and Wright (2013) for an in-depth description.

the subsidy a function of μ_t to capture the observation that the policy is contingent on the fraction of non-performing loans traded in the market.[23] To finance these expenses, the government charges a credit guarantee fee to lenders that originate loans, denoted by γ_t. We assume that to balance its budget, the government finances any deficit from implementing this policy through lump sum taxes levied on the borrower households and lenders.

Portfolio's Law of Motion. The law of motion of a lender's portfolio of loans is given by

$$b^j_{t+1} \;=\; n^j_t + (1-\phi_t)\left((1-x^j_{\ell t})b^j_t - s^j_{ht} + (x^j_{\ell t}b^j_t - s^j_{\ell t})(1-\rho) + (1-\mu_t)d^j_t\right). \tag{12}$$

The next period's portfolio comprises newly originated loans n^j_t, plus all non-maturing mortgages that remain outstanding after considering loan sales in the securitization market of high and low qualities, plus purchases of securities net of the fraction of liquidated non-performing loans—last term $(1-\mu)d^j_t$. Securitization transforms mortgage pools of heterogeneous qualities into homogeneous quality MBS, allowing security buyers to incorporate MBSs as part of their next period portfolio of assets b^j_{t+1}. This transformation provides fungibility to an MBS and constitutes a fundamental part of its liquidity value (Vickery and Wright (2013)).

Flow of Funds Constraint. The flow of funds constraint for a generic lender is given by

$$c^j_t + n^j_t(z^j_t q_t + \gamma_t) + p_t d^j_t(1-\tau_t) \leq ((1-x_{\ell t})b^j_t - s_{ht})m_{ht} + (x_{\ell t}b^j_t - s^j_{\ell t})m_{\ell t} + p_t(s^j_{ht} + s^j_{\ell t}) + d_t m_{gt} - T^L_t b^j_t, \tag{13}$$

where the left-hand side shows lender j's outflows: dividend payments c^j_t, the origination of new loans n^j_t using her idiosyncratic origination cost z^j_t. As introduced in the borrower household problem, q_t is the discounted price of new loans, and γ_t represents the per-unit guarantee fee charged to an originator.[24] The term $p_t d^j_t$ represents security purchases. The right-hand side shows the funding sources for a lender j: the first two terms represent cash inflows from maturing high- and low-quality loans after considering loan sales in the securitization market, the term $p_t(s^j_{ht} + s^j_{\ell t})$ denotes cash receipts from sales of high- and low-quality loans, and $m_{gt}d_t$ denotes cash flows from current MBSs purchases featuring a government guarantee. The last term represents a proportional tax on lenders to balance the government's budget. A lender also faces portfolio restrictions over loan sales:

$$s^j_{ht} \in [0,\ (1-x^j_{\ell t})b^j_t] \tag{14}$$

$$s^j_{\ell t} \in [0,\ x^j_{\ell t}b^j_t] \tag{15}$$

[23] The second aspect recognizes that information frictions change the debt accumulation pattern for lenders in (12), effectively changing the relative price and the incentive to purchase an MBS.

[24] In practice, the fee is a surcharge, in basis points, added to the loan interest rate contracted with the borrower. Here, we express the fee in units of the discount price q_t. See Appendix D for an analytical expression of the connection between both objects.

and it is assumed that new loans and security purchases are non-negative, $n_t^j \geq 0$ and $d_t^j \geq 0$.

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

$$V(b_t^j, z_t^j; X_t) \quad = \quad \max u(c_t^j) + \beta^L \mathbb{E}_{X_{t+1}|X_t} V(b_{t+1}^j, z_{t+1}^j; X_{t+1}) \tag{16}$$

A lender's recursive problem consists of choosing policy functions $\{c_t^j, b_{t+1}^j, d_t^j, s_{ht}^j, s_{\ell t}^j\}$ to maximize (16) subject to (12)-(15). Figure 5 in the Appendix, depicts the timeline of lenders decisions.

3.2 Borrowers

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

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

where θ represents the valuation of housing services relative to other non-housing consumption goods. The household receives a stochastic income endowment Y_t every period. In order to finance house purchases, the household takes on long-term debt (mortgages) extended by lenders. At each period t, the household begins with an outstanding stock of liabilities or mortgage debt B_t and a stock of housing H_t.

Mortgage Loans. As in practice, mortgages are modeled as long-term debt with default and prepayment risk. The debt contract is characterized by (δ, κ), where δ represents the duration of the mortgage, and κ the coupon payment on the outstanding principal $\kappa(1-\delta)$.[25] This contract structure captures the main features of the 30-year fixed-rate mortgage loans—the most prominent mortgage in the United States. New mortgage loans N_t are priced competitively at the discounted price q_t. Every period at origination, a lender gives the borrower q_t times N_t units of the numeraire good, with face value N_t, which accumulates according to the aggregate law of motion of outstanding loans given by (17).

[25] We follow the literature (Chatterjee and Eyigungor (2015); Elenev et al. (2016)), modeling mortgages as a bond-perpetuity implies that the borrower's principal debt diminishes over time and the borrower steadily accumulates housing equity. Additionally, the fixed mortgage duration (δ) feature avoids keeping track of loans of different vintages, which would add additional state variables. This structure also captures the average dynamics of mortgage cash flows for lenders and their respective shares from amortization and coupon payments.

Mortgage Default. We assume a family construct for the borrower household—as in Elenev et al. (2016) and Faria-e Castro (2022)—to model partial default in a tractable manner. Under this setup, the household is split into a continuum of members indexed by $i \in [0, 1]$. The household provides perfect consumption insurance against idiosyncratic shocks, so all members have the same allocations but differ only in their default decisions. At the beginning of every period, each member owns the same amount of housing stock h_t such that $\int_0^1 h_t di = H_t$ and the same stock of liabilities or mortgage debt b_t such that $\int_0^1 b_t di = B_t$. Then, each member draws an idiosyncratic housing valuation shock $\omega_t^i \sim G_\omega$, which proportionally lowers the value of the members' housing holdings to $\omega_t^i p_t^H h_t$ with $\omega_t^i \in [0, \infty)$. The mean, $\mu_\omega = \mathbb{E}[\omega_t^i]$, is assumed constant over time, whereas the standard deviation, $\sigma_{\omega_t} = Var[\omega_t^i]^{\frac{1}{2}}$, is assumed to vary over time. The parameter σ_{ω_t} represents mortgage credit risk in the economy and is an exogenous state variable in the model. Household members optimally decide to default on or repay their mortgage debt b_t according to the default function $\iota(\omega^i)$: $[0, \infty) \to \{0, 1\}$. When a member defaults, $\iota(\omega^i) = 1$, she also loses her stock of housing good h_t through foreclosure.[26] Appendix G.1 shows that the household's optimal default decision is characterized by a threshold $\bar{\omega}_t$—a function of endogenous and exogenous aggregate states, such that only members with $\omega_t^i \leq \bar{\omega}_t$ default on their mortgages. For a given threshold $\bar{\omega}_t$, we can define the household's aggregate default rate $\lambda(\bar{\omega}_t) = Pr[\omega_t^i \leq \bar{\omega}_t]$.

Foreclosure. Upon borrowers' default, lenders foreclose the mortgage underlying housing collateral. Foreclosure is a costly procedure for lenders, and foreclosed houses usually sell at a discount because financial institutions sell them quickly (Campbell et al. (2011)). Consequently, we assume that lenders recover a fraction $\psi \in [0, 1)$ of the market value of houses after selling them. The foreclosure recovery function per-unit of debt is given by $\Psi_t(\bar{\omega}_t) = \psi \mathbb{E}[\omega_t^i | \omega_t^i < \bar{\omega}_t] \frac{p_t^H H_t}{B_t}$, the conditional expectation represents the average housing quality of foreclosed houses.

Prepayment Risk. After default decisions, a fraction $\eta_t \in [0, 1)$ of household members that do not default face a prepayment shock that leads them to pay back their entire outstanding principal. To capture the dynamics of aggregate prepayment and macroeconomic factors, we model the prepayment rate η_t as following an exogenous process that is positively correlated with the household's income.[27] The maturity and prepayment structure imply that the

[26] This captures the loss of housing equity that a borrower experiences upon default by entering into foreclosure. We abstract from other consequences of default for a borrower, such as reputation concerns and the effect of these concerns on accessing credit over the long term.

[27] Gabaix et al. (2007) document that mortgage prepayment rates are positively correlated with consumption and income. Similarly, Chernov et al. (2017) find evidence of prepayment risk-premia in MBS arising

mortgage principal is amortized at the rate: $\phi_t = \delta(1-\eta_t)+\eta_t$. Hence, ϕ_t represents the effective maturity rate per-unit of debt after considering prepayments. Putting together these features with the dynamics of aggregate default implies the following law of motion for the stock of mortgage debt in the economy:

$$B_{t+1} = (1-\phi_t)(1-\lambda(\bar{\omega}_t))B_t + N_t, \tag{17}$$

where the first term represents the total outstanding mortgage debt net of default, and the second term represents new mortgage loans by the end of period t. Notice that going forward, a loan originated $t \geq 1$ periods in the past has exactly the same contract structure as another loan originated $t' > t$ periods in the past. Thus, we only need to keep track of total debt B_t.

Housing Market. The housing market is segmented in that only the borrower household purchases housing assets and derives utility from housing services.[28] Importantly, house prices p_t^H are determined by the borrower household's stochastic discount factor, and house price dynamics affect the household's balance sheet through housing stock holdings. They also affect households' leverage, which, in equilibrium, is key to determining households' default rate. On the credit supply side, house price dynamics are relevant for determining lenders' recovery rates from housing foreclosure and, consequently, lenders' net returns from mortgage lending, see below. For simplicity, we assume that the housing supply is fixed to $\bar{H}$ at every period.

Borrowers Budget Constraint. The household's budget constraint is given by

$$C_t + p_t^H(H_{t+1} + \Xi(H_{t+1})) + m_t(1-\lambda(\bar{\omega}_t))B_t = (1-\lambda(\bar{\omega}_t))\mu_\omega(\bar{\omega}_t)p_t^H H_t + q_t N_t + Y_t + T_t^B, \tag{18}$$

where the left-hand-side represents the household's expenses on final consumption goods C_t; purchases of new housing units for the next period $p_t^H H_{t+1}$ including a moving cost $\Xi(H_{t+1}) = H_{t+1} \cdot \frac{\nu}{2}(H_{t+1}/H_t - 1)^2$ which captures transaction costs associated with the purchase of new housing (Piazzesi and Schneider (2016)). To avoid notation cluttering, we let m_t denote the total mortgage payments made by the household family, which amounts to the sum of amortized principal and coupon payments, $m_t = \phi_t + \kappa(1-\phi_t)$. Then, $m_t(1-\lambda(\bar{\omega}_t))B_t$ represents the household's total net—of default—mortgage payments. The

from macroeconomic fluctuations—unrelated to interest rates—due to income, employment, and house price shocks.

[28] This is assumed for tractability, and it is standard in macro models with housing markets; see Greenwald (2016), and Faria-e Castro (2022). This formulation is equivalent to assuming a rigid housing demand by lenders that derive services from a constant housing stock, as in Elenev et al. (2016) and Justiniano et al. (2019).

right-hand-side of (18) shows the household's sources of income; the first term represents the market value of housing holdings—where $\mu_\omega(\bar{\omega}_t) = \mathbb{E}[\omega_t^i | \omega_t^i \geq \bar{\omega}]$ denotes the value among household's members that received a high enough valuation shock and did not default, $q_t N_t$ represents new mortgage credit, Y_t is the household's income endowment, and T_t^B represents government taxes or transfers. Notice that default affects the household's financial conditions in three ways: first, it reduces total mortgage payments; second, it reduces the remaining aggregate stock of liabilities in (17); and third, it also reduces the current aggregate stock of housing units in (18), so that the household internalizes the effects of default.

Borrowing Constraint. The borrower household faces a borrowing constraint that restricts the total amount of debt B_{t+1} at the end of the period to a fraction π of the new level of next's period choice of housing stock valued at current market prices $p_t^H H_{t+1}$. Hence, π represents loan-to-value (LTV) regulatory requirements,

$$B_{t+1} \leq \pi p_t^H H_{t+1}. \tag{19}$$

Borrowers' Recursive Problem. The endogenous states that characterize the problem of the borrower family are $\{B_t, H_t\}$. The recursive formulation is

$$V^B(B_t, H_t; X_t) \quad = \quad \max U(C_t, H_t) + \beta^B \mathbb{E}_{X_{t+1}|X_t} V^B(B_{t+1}, H_{t+1}; X_{t+1}), \tag{20}$$

where X_t denotes the set of exogenous states in the economy (to be defined later). The borrower family's problem consists of choosing policy functions $\{C_t, N_t, H_{t+1}, \{\iota_t(\omega)\}_{\omega\in[0,\infty)}\}$ to maximize (20) subject to (17)–(19).

3.3 Market Clearing

State Variables. The set of aggregate states in the economy is given by $X_t = \{Y_t, \eta_t, \sigma_{\omega_t}, \Gamma_t, B_t, H_t\}$. Recall that $\{Y_t, \eta_t, \sigma_{\omega_t}\}$ are exogenous states representing the borrower household's income endowment, the household's prepayment shock, and the volatility of the housing valuation shocks, respectively. We model these exogenous shocks as following Markov processes, see appendix D.1 for estimation details. The expression $\Gamma_t(b, z)$ is the joint distribution of the stock of loans and origination costs across lenders.[29] The variables $\{B_t, H_t\}$ are the aggregate stock of loans and the aggregate stock of housing in the economy, respectively.

[29]In the presence of aggregate shocks, agents need to know Γ_t to forecast prices. The distribution becomes a state variable because prices are a function of aggregates, which are computed using Γ_t (see Krusell and Smith (1998)).

Market clearing in the housing market requires

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

Market clearing in the credit market requires aggregate lending supply that meets aggregate lending demand from households:

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

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

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

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

The government budget constraint is given by

$$\gamma_t N_t + T_t^B + T_t^L B_t = \tau_t p_t D_t + m_{gt} - m_{dt}, \tag{24}$$

where $\gamma_t N_t$ represents aggregate government revenue from collecting the guarantee fee. T_t^B and $T_t^L B_t$ are a lump-sum tax charged to borrowers and a proportional tax to lenders, respectively. We assume that the government balances its budget each period. The right-hand side represents government expenditures from insuring cash flows of guaranteed MBSs and from providing subsidy τ_t to security buyers, and D_t is the aggregate demand of securities.

The aggregate resource constraint is given by

$$C_t + \int c_t^j d\Gamma_t(b, z) + p_t^H (H_{t+1} + \Xi(H_{t+1})) - (1 - \lambda(\bar{\omega}_t))\mu_\omega(\bar{\omega}_t) p_t^H H_t - \lambda(\bar{\omega}_t)\Psi_t B_t + q_t \int (z_t^j - 1) n_t^j d\Gamma_t(b, z) \leq Y_t, \tag{25}$$

where $q_t \int (z_t^j - 1) n_t^j \, d\Gamma_t(b, z)$ represents the aggregate cost of lending in the economy. From here onward, to ease the notation, the superscript j is suppressed, and lowercase variables represent individual lender decisions. Time indexing is suppressed for variables in t, and variables in $t+1$ are indicated by the superscript $'$.

3.4 Competitive Equilibrium

A recursive competitive equilibrium given government policy $\{\gamma, \tau, T^B, T^L\}$ consists of value function $V^B(B, H; X)$ and policy functions for the borrower household $\{C, N, B', H', \{\iota_t(\omega)\}_{\omega \in [0, \infty)}\}$, value function $V(b, z; X)$ and policy functions $\{c, b', d, s_h, s_\ell\}$ for lenders $j \in J$, aggregate law of motion for Γ', the fraction of securitized non-performing loans $\{\mu\}$, and price functions $\{q, p, p^H\}$ such that:

1. Borrowers' policy functions solve the problem in (20), taking as given $\{q, p, p^H\}$.

2. Lenders' policy functions solve the problem in (16), taking as given $\{q, p, \mu\}$.

3. The housing price p^H clears the housing market: (21).

4. The price of lending $q > 0$ clears the credit market: (22).

5. Whenever the securitization market is active, there is an equilibrium price p that clears the securitization market (23) and the fraction of traded non-performing loans μ is given by (11).

6. The aggregate fraction of non-performing low-quality loans in the economy equals the aggregate household's default in (10) every period.

7. The aggregate law of motion for Γ' is generated by the Markov processes of exogenous shocks, the distribution of lenders' idiosyncratic shocks $F(z)$, and lenders' policy functions b'.

8. The government budget constraint (24) is satisfied every period.

9. The resource constraint (25) holds every period.

4 Quantitative Analysis

4.1 Calibration and Estimation

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

Borrower Preferences and Housing. The borrowers' discount rate β^B is set to 0.97 to match the ratio of consumption expenditures, including non-durables and services, to the disposable personal income from the national income and product accounts (NIPA), which equals 0.79. The housing preference parameter θ is set to 0.22 to match the ratio of residential mortgage credit to residential real estate: 0.14 from the U.S. Financial Accounts, also known as the Flow of Funds (FoF). We set ν to 3.5, replicating a moving transaction cost of 6% of the housing market value (Piazzesi and Schneider (2016)). The loan-to-value ratio π is set to 0.80 to match the average LTV on first lien mortgages across all originators, banks and non-banks, from the National Mortgage Database (NMDB). We set the mean of borrowers' housing valuation shocks μ_ω to 0.971. This matches the average depreciation rate, 2.91%, of private residential capital across all types of housing units, including alterations and major replacements, from the Bureau of Economic Analysis (BEA).

Mortgages, Prepayment and Default Risk. We capture the characteristics of 30-year fixed-rate mortgages, the most common mortgage contract in the U.S., by setting the fixed duration parameter δ to 0.03 and the coupon rate κ to 0.05. As in practice, households can prepay and default on their mortgages. Motivated by Gabaix et al. (2007), we let the prepayment η_t be a function of the average prepayment rate and an exogenous disturbance ϵ_η that correlates with households' income (see Appendix D.1 for details).[30] The mean prepayment rate $\bar{\eta}$ is set to 0.12 and its standard deviation to 0.03 to match the historical prepayment rate of conventional 30-year fixed-rate mortgages as reported by Fannie Mae and Freddie Mac from SIFMA. The maturity structure and the prepayment process imply an effective duration of 7.25 years for the mortgage bond in the model in line with empirical estimates (Walentin (2014)). The cross-sectional variance of the housing valuation shocks σ^2_ω is an aggregate state directly affecting borrowers' default risk dynamics. As a data counterpart, we estimate the cross-sectional variance of house price growth using house price index data from the FHFA for all 51 states from 1975 to 2020. We split the sample into low-and high-volatility regimes and estimate a first-order Markov process for each regime.[31] Appendix D.1 reports the estimated state spaces and transition matrices. Our estimated state space for the low-volatility regime, together with the income process (see below) and prepayment process, replicate an untargeted default rate of 0.98% in normal times for the benchmark economy. 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, so we calibrate the two highest housing valuation shock states to obtain a default rate of 4.35% in crisis times and unconditional default rates of 2.04% in line with the national 90 days or more delinquency rate from NMDB; see Table 2.[32]

Borrowers Income Risk. We use the cyclical component of the Gross Domestic Product

[30] 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.

[31] Our approach extends the work of Elenev et al. (2016), who presented a similar framework for modeling $\sigma^2_{t,\omega}$ to capture exogenous forces affecting mortgage credit risk that fit high-volatility episodes like the foreclosure crises experienced in 2007-12. However, our key distinction lies in utilizing accessible data on house price indexes to estimate the underlying process.

[32] The delinquency rate includes all residential mortgages classified as 90 days or more past due, in foreclosure, or associated with bankruptcy at the end of the year. For more information, see the NMDB from the FHFA.

(GDP) for the borrower household's income Y. We follow Elenev et al. (2016) in combining the processes for the cross-sectional variance of housing valuation shocks with the income process into a joint first-order Markov process. Our process replicates a recession probability of 0.34, in line with the long-term NBER frequency of recessions. In our setup, mortgage crises are recessions characterized by negative income shocks and high-housing risk, as such episodes can generate waves of mortgage default similar to the data. In a long simulation, our model replicates a probability of a mortgage crisis of 0.082, which implies that about 1/4 of recessions are crises related to the financial sector, consistent with the findings in Jordà et al. (2013, 2016).[33]

Housing Foreclosure. We set the recovery fraction from foreclosure ψ equal to 0.65 in normal times and 0.50 in crisis times to match the liquidation costs lenders face during the foreclosure process. These housing recovery rates, together with the housing valuation shocks, generate severity rates of 34.6% in normal times and 49.8% in crisis times, in line with the observed severity rates for loans with 80% LTV as reported by Fannie Mae and Freddie Mac (Urban Institute) and with the values estimated in the literature (Campbell et al. (2011)). Combining severities with the default rates yields net-loss rates to lenders of 0.8% and 2.2% during normal and crisis times, respectively. There is a less direct data counterpart for ρ, the probability of low-quality loans that enter foreclosure. However, since this parameter governs the degree of lenders information advantage and, consequently, the fraction of securitized loans, we set ρ equal to 0.82 to match the average fraction of loans sold into securitization by large originators from 1990 to 2018, according to HMDA.

Lenders Technology. The distribution of origination cost across lenders, $F(z)$, is modeled as a generalized beta distribution characterized by shape parameters (s_1, s_2) with support $[\underline{z}, \bar{z}]$. Since this object does not have a direct data counterpart, we estimate—by the simulated method of moments (SMM)—the underlying parameters of $F(z)$ to match the market share of the third and fourth quartiles of the cross-sectional distribution of mortgage lending. These are key moments obtained from the HMDA panel of mortgage originators that spans the period from 1990 to 2017.[34] The support of the distribution is obtained by normalizing the scale $sc = \bar{z} - \underline{z}$ to 1 and by setting the location parameter $lc = \underline{z}$ to match the level of

[33] Jordà et al. (2013) and Jordà et al. (2016) construct granular historical datasets for advanced economies covering recession episodes since 1870. The authors document that one fourth of recessions are linked to a financial crisis and that mortgage lending dynamics are key drivers of financial-crisis recessions.

[34] The choice of moments is motivated by the analysis in Section ?? (see Table ??). The HMDA dataset requires all mortgage originators to collect and publicly disclose information about applications for, originations of, and purchases of new homes, home improvement, and refinancing loans.

Table 1: Calibration for the benchmark economy

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

mortgage spread to the 10 years Treasury bill from 1990–2018. The non-targeted moments in Table 2, show that the model also fits well the fraction of small mortgage originators in the cross-section, as well as the market shares of the second and first quartiles of the distribution of mortgage lending.

Government Policy. The government's vector of policy instruments is given by $\{\gamma, \tau\}$. For the benchmark economy, we calibrate the credit guarantee fee, γ, to 20 basis points corresponding to the average origination fee Fannie Mae and Freddie Mac charged before the Great Financial Crisis. The appendix D.1 shows the expression for γ as a function of the credit guarantee quoted in basis points. For the coverage of credit guarantees, we first calibrate the benchmark economy to a partially insured securitization market— consistent with the pre-GFC period from 1990 to 2006, when private securitization played an important role. Consider $\tau_t = \alpha\mu_t$, where $\alpha \in [0, 1]$ corresponds to the coverage of credit guarantees provided by the government policy, and μ_t is the fraction of securitized non-performing loans in (11) that endogenously maps household's credit risk. When $\alpha = 1$, the policy completely offsets a security buyer's losses arising from default in the underlying pool of mortgages; hence, $\tau_t = \mu_t$ works as a full credit guarantee policy. In contrast, when $\alpha = 0$, there is a complete transfer of the household's credit risk to investors (i.e., $\tau_t = 0$). For the benchmark economy we set $\alpha = 0.6$ consistent with the market share of agency securitization pre-GFC.[35] In section 4.4, where we look at the economy post-GFC, we set $\alpha = 1$ to study the dynamics of the current securitization market. In the benchmark economy, any deficit arising from the operation of the credit guarantee scheme is financed by lump-sum taxes levied on borrowers and lenders in equal proportions. Hence, taxes T_t^B and T_t^L in (24) are the same for borrowers and lenders and add up to the policy deficit. For the analysis of the post-GFC economy, we relax this assumption and compute the break-even credit-guarantee fee that brings the deficit to zero.

Non-targeted moments. The model fits the data well. Both targeted and non-targeted moments are close to the data counterparts. The second part of Table 2 shows that the model generates a high and positive correlation between the volume of credit and security issuance, as in the data. This correlation is the outcome of the endogenous liquidity securitization channel ingrained in the model. Other correlations of interest are the negative correlation between household default and the growth rate of mortgage lending and the positive correlation between household default and the mortgage spread, which are close to the data.

[35]Our approach deliberately focuses on an aggregate perspective of the securitization market without explicitly modeling the complexities of market segmentation. After the GFC, the non-agency segment has become small, representing no more than 5% of total issuance in the RMBS market; see Figure 8 in the Appendix.

Table 2: Targeted and Non-targeted Moments

Targeted Moments

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

Non-targeted Moments

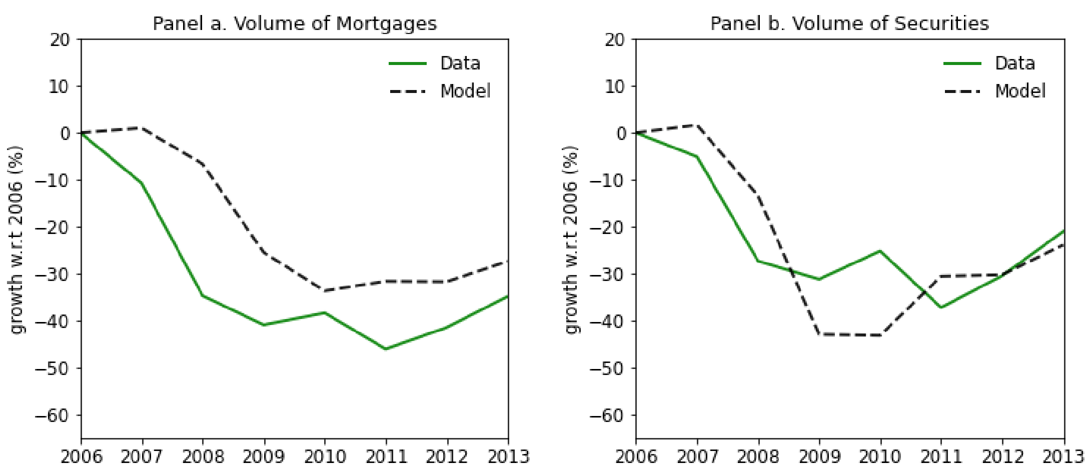
Variable	Model	Data	Description
Default rate - normal times (pp)	0.98	1.20	Mortg. deliquency (90 days + foreclosure). NMDB, 90-06.
Mortg. effective duration	7.25	7.50	Effective duration of 30y fixed-rate mortgages. Walentin (2014)
Market shares Q1	0.000	0.002	Cross-section mortgage lenders. HMDA, 90-18.
Market shares Q2	0.002	0.008	Cross-section mortgage lenders. HMDA, 90-18.
Fraction of small lenders	0.84	0.91	Fraction of lenders originating less than the average. HMDA, 90-18.
Corr(security issn, lending issn)	0.92	0.98	TS correlation for RMBS issuance and mortgage lending (HDMA).
Corr(hhs default, lending growth)	-0.17	-0.35	TS correlation households delinquency and mortgage lending growt
Corr(hhs default, mortg spread)	0.90	0.53	TS correlation households delinquency and mortgage spread.

4.2 An application to the Great Financial Crises

Dynamic Responses. This section studies the model's predictions on aggregates in the mortgage market during the GFC. Our first experiment consists in simulating the model, under the benchmark calibration, for the sequence of realized shocks of GDP (aggregate household income) and a sequence of housing valuation shocks that endogenously matches the default rates observed from 2006 to 2016. Figure 10 in Appendix B shows the entire sequences since 2000.

The model accounts for two-thirds of the 40.6 percent contraction in aggregate residential mortgage lending observed from 2008 to 2013. Figure 3 shows the percentage changes in the volume of new mortgage lending and the volume of issuance of MBS (right panel) with respect to 2006. The model's success in generating large fluctuations rests on two factors. The first factor is the endogenous information frictions multiplier that amplifies the effects of household shocks; we delve deeper into this in the following section. The second is the characteristics of the cross-sectional distribution of mortgage lending. The estimated density for lenders' origination costs, $F(z)$, displays a small mass of low-cost and a large mass of high-cost lenders in order to fit well the structure of the cross-sectional distribution of mortgage lending—a small mass of lenders accounting for a large fraction of lending in the market. This structural feature of the U.S. mortgage market informs the model about equilibrium prices and quantities. Importantly, it indicates that the liquidity benefits of trading in the securitization market are significant and that mortgage originators depend highly on liquidity from securitization. This feature is 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 more recently by Jiang et al. (2020). Thus, the cross-sectional data plays a key role in informing the model's quantitative magnitude of induced fluctuations.

Figure 3: The mortgage market during the Great Financial Crisis



Panel a: *Data* is the aggregate volume of new mortgage issuance in U.S. dollar amounts. Source: HMDA database. Panel b. Data correspond to the volume of Residential Mortgage-backed security issuance U.S. dollar amounts. Source: SIFMA database. All variables are expressed in growth rate with respect to 2006 in two years moving average window. *Model* corresponds to the benchmark economy simulated for the sequence of household income and housing volatility shocks observed in the data.

Based on this market structure, the model predicts that fluctuations in the aggregate default rate induce changes in the composition of lenders—sellers, holders, and buyers, which in turn can induce large fluctuations in aggregate credit. In particular, severe episodes of negative households income and housing shocks lead to spikes in mortgage default which lowers the average quality of securities traded and, ultimately, results in large contractions in the volume of new mortgage lending because some of the most efficient lenders—originating a large share of new mortgages—switch from securitizing their entire portfolio to securitizing a small fraction of it. In other words, the composition of mortgage originators endogenously changes towards a lower mass of lender-sellers and a larger mass of lender-holders as the securitization market becomes less liquid. Since lenders depend on securitization liquidity to issue new mortgage lending, the mortgage rate increases and aggregate credit contracts. The model predictions for other households aggregates: house price growth, the mortgage spread, and aggregate consumption of non-durable goods are also in line with the observed dynamics in the data during this period; see Figure 12 in Appendix E.

In the securitization market, the aggregate volume of MBS issuance fell by 30 percent on average between 2008 and 2013. The model predicts an average decline of 32.5 percent during the same period, see Figure 3. The model predicted contraction for the years 2009 and 2010 goes beyond the aggregate MBS contraction observed in the data. This difference arises from the "large-scale assets purchase programs" of GSEs MBSs carried out by the U.S. Federal Reserve System and the Treasury Department from September 2008 to December 2010. Naturally, as the model ignores these events it predicts a stronger security issuance decline.[36]

It is worth noting that although the MBSs issuance contracted in the aggregate during this period, the performance by securitization segments was widely different. Government interventions allowed credit guarantee securitization by GSEs—the agency segment—to continue almost uninterrupted.[37] In contrast, the non-agency securitization collapsed almost completely, as shown by Figure **??** in section **??**. Our model does not explicitly consider such

[36]In September 2008, Freddie Mac and Fannie Mae were placed into conservatorship by the FHFA as part of a plan to stabilize the residential mortgage market that also included a large-scale asset purchase program by the Federal Reserve System and senior preferred stock purchased agreements by the Treasury Department. Purchases of Freddie Mac and Fannie Mae's MBSs by the Treasury Department amounted to $221 billion, while Fed purchases amounted to $1,250 billion, as reported by the FHFA.

[37]The two major GSEs, Fannie Mae and Freddie Mac, suffered significant credit losses during the financial crisis. It is widely acknowledged that their securitization operations would have been severely impaired had they not been placed under conservatorship; Frame et al. (2015) describe in detail the financial position of GSEs during this period.

market segmentation; however, its predictions align with the aggregate market dynamics given the significant proportion of investors exposed to household credit risk through non-agency securitization before and up to the GFC. Figure 13 assesses the dynamics of aggregate credit and security issuance for a fully credit-guaranteed securitization market. In this case, the induced credit contraction is less severe than in the benchmark economy, and the securitization market displays a muted response to increases in mortgage default. Both dynamics are consistent with the observed behavior of the agency-dominated market segment, where investors face limited exposure to household credit risk.

4.3 Quantifying Information Frictions

How important are information frictions in accounting for fluctuations in aggregate credit? To answer this question, we decompose the forces underlying the dynamics responses in Figure 3. The main idea of our decomposition is to isolate the impact of information frictions in the transmission of household income and housing shocks.

First, in Appendix F, we design a comparable complete information economy featuring similar distortions and government policies as the benchmark economy with private information. We simulate both economies for the identical sequences of income and housing volatility shocks presented in Figure 10. The dynamic responses of aggregate credit and securitization volumes from each economy compared to their data counterparts are shown in Figure 14 in the Appendix. Information frictions played an important role in amplifying household shocks during the GFC episode; we measure that information frictions amplified the mortgage credit contraction by a factor ranging between 1.2 to 1.3 with respect to an economy that abstracts from such frictions in the securitization market.[38] The multiplier corresponds to the ratio of the average contraction in aggregates predicted by the benchmark economy to that of the complete information economy from 2008 to 2013, see Table 9 in the Appendix. Notably, the amplification effects of information frictions rise as lenders' ability to identify non-performing low-quality loans increases, captured by ρ.

Shock Decomposition. The decomposition of shocks is presented in Figure 4. The difference in the responses of the aggregates—credit and security issuance volumes—between economies corresponds to the contribution of information frictions and is represented by the

[38]Large amplification effects from the securitization liquidity channel have also been documented at the micro level (Calem et al. (2013)) find that the contraction in mortgage credit by commercial banks that were highly exposed to securitization liquidity was six times greater than that of similar banks that were not dependent on securitization during the collapse of the non-agency RMBS market.

orange bars. The contributions of the income and prepayment shocks are jointly represented by the blue bars. In comparison, the yellow bars represent the contribution of the housing volatility shocks. Each contribution is obtained by simulating the comparable complete information economy for one shock at a time while keeping the other shocks at their unconditional mean. Given the strong nonlinearities present in the model, the individual contributions do not add to the joint effect of all shocks, represented by the continuous black line.

Figure 4: Shock Decomposition during the Great Financial Crisis

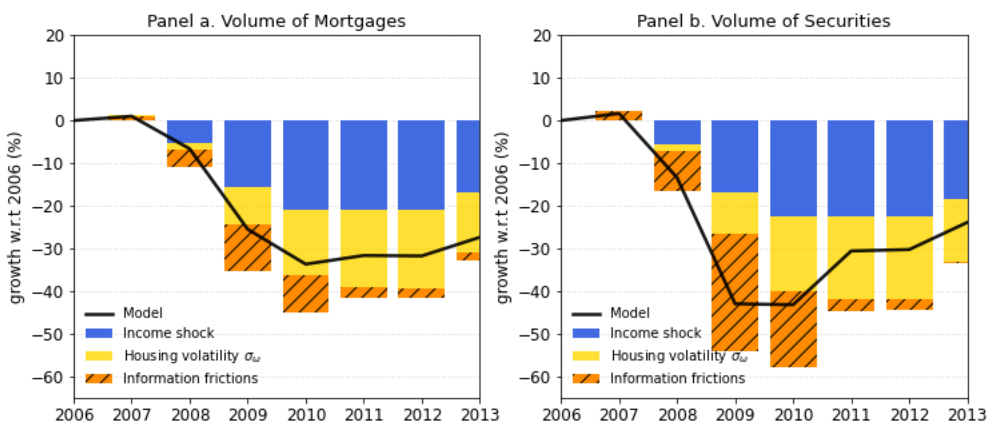


Table 3: Decomposing the average contraction, 2008-13

Aggregates	Info-frictions	Housing σ_ω^2	Income Y	Data
Volume of Mortgages	-5.1	-12.7	-16.6	-40.6
Volume of Securities	-10.1	-13.8	-17.9	-29.8

Table 3 shows that, on average, one-fifth of the model's predicted decline in mortgage lending arises from the amplification effect of information frictions on household shocks, while housing and income shocks account for the rest. Our results are consistent with those of models—albeit those not specific to the mortgage market—that study the aggregate amplification effects of information frictions in asset markets through liquidity channels (see Krishnamurthy (2010), Kurlat (2013), Bigio (2015), and Asriyan (2020)).

4.4 Evaluating the Current Securitization Market

The Post-GFC Economy. After the GFC, two main changes took place in the securitization mortgage market. A first-order structural change was the collapse of the non-agency

MBS segment, which effectively left only the agency MBS segment in place from 2008 onward. Consistent with such a structural change, we let $\alpha = 1$, so the securitization market resembles the current fully credit-guaranteed agency securitization market. The second change was the increment of the guarantee fee γ charged by GSEs to mortgage originators. After 2012, this fee increased from 20 to 60 basis points on average—see Figure 9—to bring the price of credit guarantees closer to a (private) market pricing of mortgage credit risk.[39] We introduce these two changes to government policy in the model, while keeping the rest of the parameters unchanged and label it the post-GFC economy. We also use the model to compute the break-even guarantee fee, i.e., the endogenous guarantee fee that generates enough revenues to finance the credit guarantee policy without generating any deficit. Table 4 reports selected statistics from a long simulation for the benchmark economy, the post-GFC economy, and an alternative version of the post-GFC economy with the break-even guarantee fee.

Overall, the model predicts a mortgage spread in the post-GFC economy settling closely above the initial level of the benchmark economy. Two opposing forces account for this; on one side, the increase in the guarantee fee pushes mortgage rates up; on the other, increasing the guarantee coverage reduces intermediation costs as assets are reallocated more efficiently in the securitization market. The direction is consistent with the observed patterns of the mortgage spread in the data between the periods 1990–2006 and 2013–2018, as shown in Table 6 in Appendix B. Our model predicts, a higher volatility of the mortgage spread compared to the benchmark. This pattern arises because lower mortgage rates induce the borrower household to consume more housing goods, driving up their stock of mortgage debt and leverage, consequently, in equilibrium we observe higher mortgage severity and default rates than the benchmark pre-GFC economy. In the securitization market, the volatility of the price of securities experiences a similar increase as mortgage spreads since security prices still fluctuate due to the general equilibrium effect from borrowers' credit demand. Having a fully credit guaranteed securitization market induces more lenders to trade, purchasing securities or securitizing their entire portfolio, the average fraction securitized increases in the post-GFC economy—consistent with the patterns observed in the data, see Figure 6. The information friction multiplier dampens and so does the probability of market collapse, which falls from 11.9% in the benchmark economy to 0.51% in the Post-GFC economy.

Pricing Credit Guarantees. Pricing credit guarantees adequately to reflect households'

[39]Starting in 2011, the FHFA has instructed both GSEs to raise the guarantee fee several times. For instance, the August-2012 FHFA press release argues: "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."

Table 4: Comparing Economies after the Great Financial Crisis

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

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

credit risk and sustainably finance the credit guarantee policy has been at the forefront of the policy discussion during the last decade. Our model indicates that although the price of credit guarantees increased three-fold and generated higher revenues in the post-GFC economy, the expansionary coverage of credit guarantees also implies higher expenses. Leaving the deficit above the benchmark economy and suggesting the credit guarantees are still underpriced. Using our model, we estimate a break-even guarantee fee of 145 basis points for the post-GFC economy. Such an estimate incorporates the amplification effects of information frictions, which we have demonstrated are essential to account for the dynamics of the aggregate volumes of credit and security issuance in the U.S. mortgage market.[40] Column

[40]Our result complements other studies of the GSEs' credit guarantee policies. Elenev et al. (2016) study the interplay between the pricing of credit risk guarantees and the deposit-insurance schemes in a model of

3 of Table 4 shows the simulated moments for the post-GFC economy with the break-even guarantee fee. Comparing mortgage rates across columns 2 and 3, we see that mortgage rates increase less than proportionally to the increase in the guarantee fee. In this case, although mortgage rates initially increase, the general equilibrium effects of higher mortgage rates reduce borrowers' indebtedness and default risk, ultimately lowering mortgage spreads.

It is important to note that household income and housing volatility processes remain unchanged for all economies, and so does the frequency of mortgage crises. However, several notable differences emerge when comparing the economy in column 2 to the one with higher break-even guarantee fees. The economy with higher guarantee fees exhibits relatively lower household debt levels compared to the post-GFC one, lower mortgage default rates, and decreased net mortgage losses. The credit guarantee policy does not generate deficits, so households do not face additional taxes, which, coupled with lower default and foreclosures, allows them to expand their consumption of non-durable goods. These effects spill over into the securitization market, lowering the probability of market collapses.

Welfare. Borrowers and lenders are better off in the post-GFC economies than in the benchmark economy. Table 8 in Appendix E shows that the post-GFC economy produces small welfare gains for borrowers and lenders, in consumption equivalent units. Borrowers' welfare gains come mainly from lower mortgage rates and expanded housing consumption. While for lenders, it is the improvement in allocative efficiency of the securitization market which generates welfare gains. A well-functioning securitization market reduces intermediation costs and increases risk sharing among lenders; consequently, lenders' dividend consumption increases. Introducing a break-even guarantee fee increases borrowers' welfare gains and slightly reduces those of lenders. The economy with a break-even guarantee fee displays additional welfare gains for borrowers by lowering mortgage default, housing equity losses and tax payments. For lenders, higher guarantee fees reduce dividend payments; however, they benefit from a lower dead-weight-loss from mortgage foreclosures and a less volatile market.

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

First, a primary concern is the potential moral hazard in mortgage origination associated with offering a complete credit guarantee, as it reduces lenders' incentives to monitor due

banking featuring moral hazard in banks' leverage decisions. Similarly, the authors find that credit guarantees are still underpriced in the post-GFC economy.

to the ability to transfer risk away from their balance sheets (Gorton and Metrick (2013)). However, these concerns have been mitigated in recent years as the GSEs have undertaken significant operational changes that reduce the impact of information frictions on their securitization activities. Conforming requirements for the purchases of loans have tightened, demanding higher LTV and credit scores for borrowers. For lenders, continuous scrutiny and monitoring of loan purchases, as well as stricter enforcement of representations-and-warranties have contributed to reducing mortgage fraud and misrepresentation of loan terms and improving the credit quality of their guaranteed portfolios. Exploring the relationship between moral hazard incentives during loan origination and adverse selection in securitization presents a promising area of research. Parlour and Plantin (2008), Vanasco (2017), and Caramp (2019) provide theoretical insights into the interplay between asset quality screening and adverse selection in secondary markets. Extending our current model, which already incorporates key features of the securitization market, to include originators' screening incentives could yield valuable quantitative insights.

A second crucial concern regarding the credit guarantee policy is the significant concentration of credit risk in a single party. The exposure of GSEs to borrowers' credit risk is substantial; as of 2022, Fannie Mae and Freddie Mac own or guarantee $5.6 trillion in residential mortgages (Federal Housing Finance Agency). Since 2013, the GSEs have been exploring limited-scale operations to transfer their credit risk exposure to the private sector through Credit Risk Transfers (CRT). This involves the issuance of Mortgage-Backed Securities (MBS) with a tranching structure, allowing for the sharing of credit losses between private investors and the GSEs during periods of heightened mortgage defaults. Finkelstein et al. (2018) describe the range of risk transfer instruments and operations the GSEs have experimented with during the last decade. However, this initiative is still in its early stages, with CRT securities representing only 5.1 percent of the agencies' total market size by 2017 (Finkelstein et al. (2018)). In this regard, several research questions arise, such as the feasibility of scaling up CRT, the resilience of such initiative during severe financial distress episodes like those witnessed during the Global Financial Crisis (GFC), and the appropriate equity capital structure for the GSEs.

5 Discussion and Conclusion

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

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

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

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Appendix to Mortgage Securitization and Information Frictions in General Equilibrium

A Data Sources

Home Mortgage Disclosure Act - HMDA

Here I describe the details about the data set and the construction of variables used in the analysis of Section ??. HMDA requires mortgage originators, banks and non-bank institutions, to collect and publicly disclose information about their mortgage lending activity. The information includes characteristics of the mortgage loan an institution originate or purchase during a calendar year. HMDA is estimated to represent the near universe of home lending in the United States, see Neil et al. (2017). I construct a panel of mortgage originator-institutions for the period 1990-2018. First, I use the Loan Application Registries(LAR) to compute aggregate volumes, in dollar amount and loan counts, of mortgages originated and mortgages sold in the securitization market every year for every reporter institution. As is standard in the literature, I restrict the sample to conventional, one-to-four family, owner-occupied dwellings, and include both home purchases and refinanced mortgage loans. Second, I use the HMDA Reporter Panel which contain the records of originator-institutions (reporter). Variables of interest are the type of institution (Bank Holding Company, Independent Mortgage Company, Affiliate Mortgage Company), the institution supervisory government agency, and assets. Finally, I merge the collapsed LARs dataset with the Panel of Reporters using the unique reporter ID. From 1990 to 2018 the HMDA panel covers 8,127 mortgage reporters every year on average.

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

Households Income. The filtered, Hodrick-Prescott, cyclical component of GDP.

Default rates. Corresponds to the national delinquency rate for mortgage loans that are 90 or more days delinquent or went into foreclosure. Source: National Mortgage Database (NMDB).

Mortgage Interest rates. I use the average 30 year fixed mortgage rate from Freddie

Table 5: Description of HMDA LAR and Reporter Panel files

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

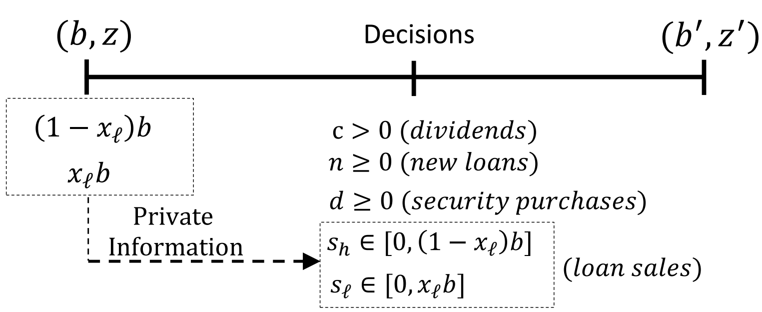
Mac Primary Mortgage Market Survey 2018.

Guarantee Fees. Taken from Fannie Mae and Freddie Mac Single-Family Guarantee Fees Reports provided by the Federal Housing and Finance Administration (FHFA). Source: https://www.fhfa.gov/AboutUs/Reports.

B Additional Figures and Tables

B.1 Timeline for lenders decisions

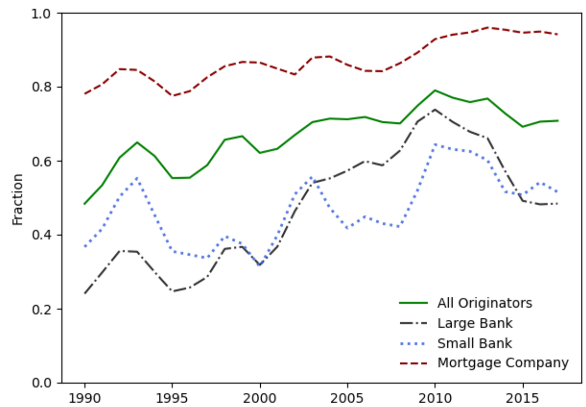
Figure 5: Timeline for lenders decisions



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

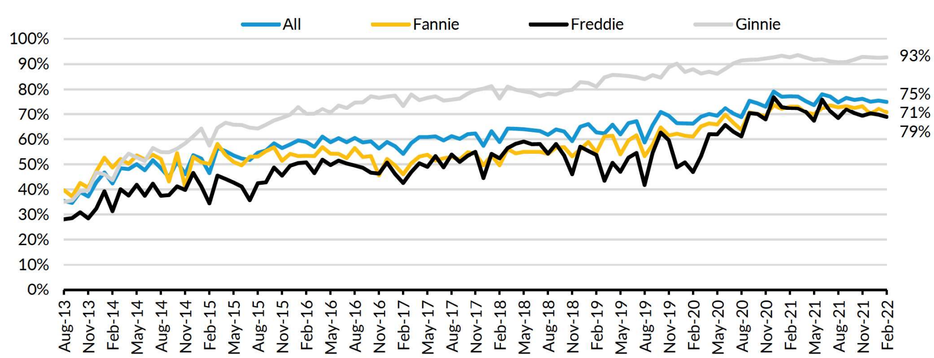
B.2 Features of the U.S. mortgage market

Figure 6: Fraction securitized



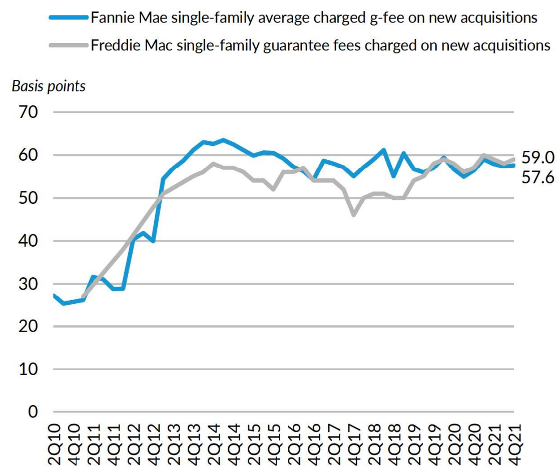
Source: HMDA LARs and Reporter Panel 1990-2018. The fraction of sold or securitized corresponds to the cross-sectional average aggregate dollar amount of mortgage sold/securitized divided by the aggregate dollar amount of lending for a mortgage reporter institution for loans originated within the year that is reported. Large banks are depository institutions with assets greater or equal to 1 billion dollars. Small banks are depository institutions with assets of less than 1 billion dollars.

Figure 7: Non-bank origination share of agency residential mortgage lending.



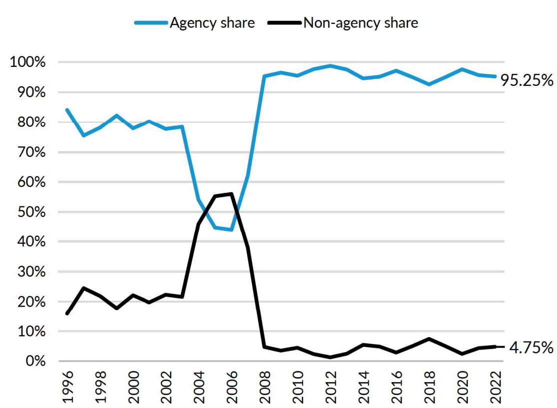
Source: Urban Institute. Reproduced from the Urban Institute Housing Finance Chartbook, March 2022. Non-bank institutions include affiliated and independent mortgage companies.

Figure 9: Effective Guarantee fees



Source: Freddie Mac, Fannie Mae, and Urban Institute.
Reproduced from the Urban Institute Housing Finance Chartbook, March 2022. The figure shows the average guarantee fees charge by Freddie Mac and Fannie Mae on mortgage purchases from mortgage originators.

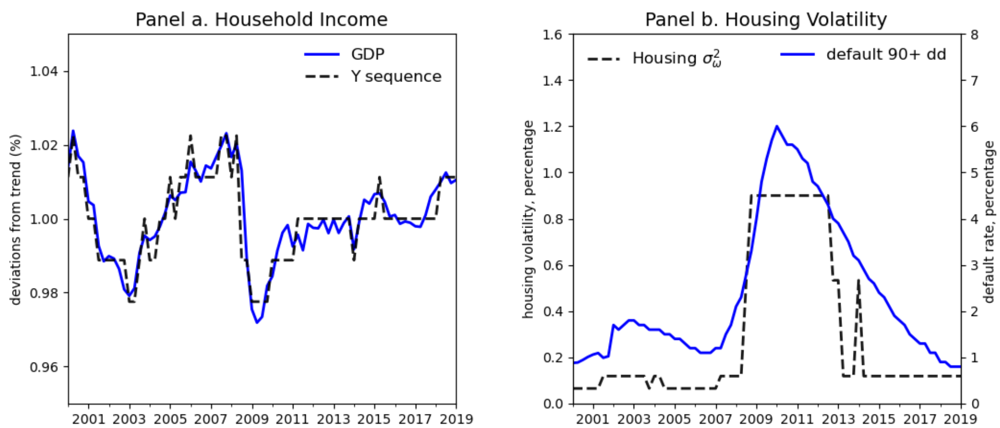
Figure 8: Agency/Non-agency share of residential MBS issuance



Source: Inside Mortgage and Urban Institute.
Reproduced from the Urban Institute Housing Finance Chartbook, March 2022. Agency corresponds to MBS issuance by the Government Sponsored Enterprises Freddie Mac and Fannie Mae. Non-agency corresponds to private securitizers.

B.3 Households Income and Default Rates

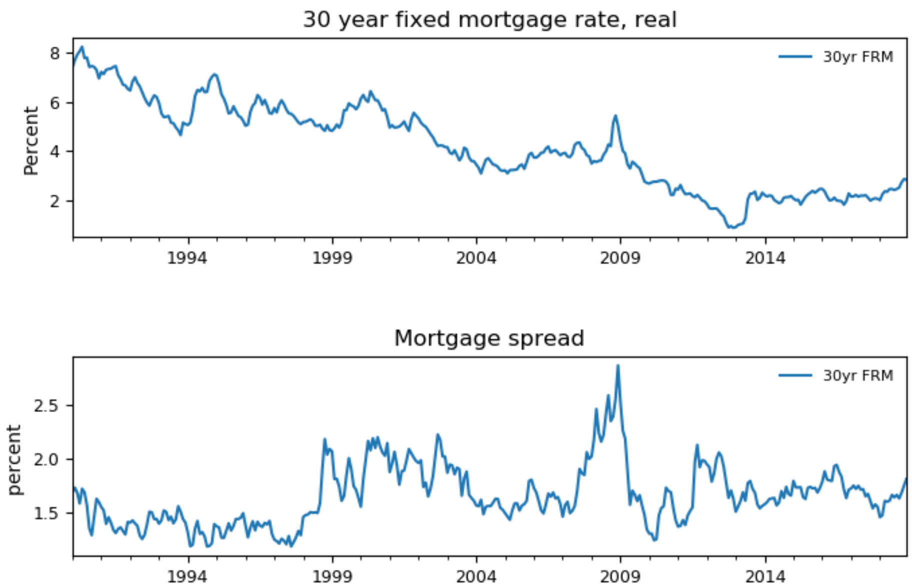
Figure 10: Income and default processes



Panel a. Household Income corresponds to the cyclical component of Disposable Personal Income from NIPA.
Panel b. The sequence of housing valuation shocks matches the moments of household's aggregate default rate. The default rate is the percentage of delinquent single-family residential mortgage loans 30 days or more, or in foreclosure, reported by all commercial banks. Source: Federal Reserve St Louis Fed (FRED) and Federal Financial Institutions Examination Council (FFIEC) Consolidated Reports of Condition and Income.

B.3.1 Mortgage Interest Rates

Figure 11: Historic mortgage interest rates



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

Table 6: Historic average mortgage rates

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

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

C Computational Algorithm

C.1 Solving the General Equilibrium Model

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

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

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

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

C.2 Welfare evaluation

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

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

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

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

D Calibration Appendix

D.1 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 cyclical component of GDP to estimate the state space and transition matrix. First, we estimate an auto-regressive model of first order, AR(1), for a long-time series from 1960 to 2019. We discretize this processes by the Rouwenhorst method into a Markov chain with seven states:

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

with the corresponding transition probability matrix Π_Y,

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

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

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

with transition probability matrix

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

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

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

with transition probability matrix

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

We then combine the high-volatility state space for the housing valuation shocks with the three lowest states of the income process and the low-volatility state space with the top four income states. Thus, the joint distribution for income and housing shocks features 21 states. Table 7 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 7: Fitted moments for income and housing volatility processes

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

Prepayment risk. Mortgage prepayments occur for various reasons: moving to a different house, saving in interest payments (reducing the debt burden), refinancing debt to benefit from lower interest rates, or refinancing to take on more debt (cash-out). We abstract from modeling the household prepayment decisions and introduce prepayment risk as an exogenous process positively correlated with the household's income.[41] Our specification, although reduced form, captures a household's prepayment risk arising from paying off mortgages to save in interest payments and from housing moving motives. Motivated by Gabaix et al. (2007), who conceptualized prepayment uncertainty as an error surrounding the average

[41] 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.

prepayment forecast, we let households' prepayment rates follow an analogous exogenous process:

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

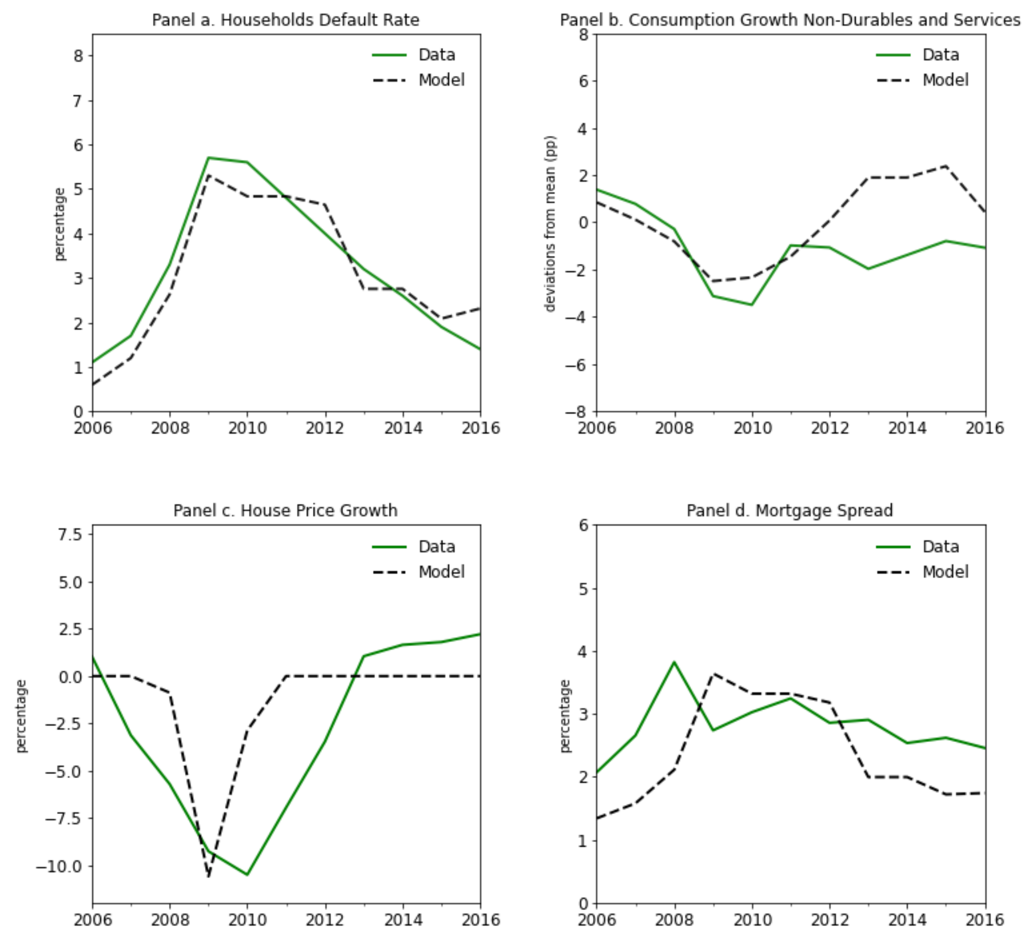
where $\bar{\eta}_t$ denotes the average prepayment rate and ϵ_η represents disturbances that correlate with household income. Based on SIFMA reports—"Long Term for conventional 30-yr mortgages with a coupon of 5% from Fannie Mae and Freddie Mac and Ginnie Mae—we set $\bar{\eta} = 0.12$ and let $\epsilon_\eta \in [-0.03, 0.0, 0.03]$ be a three-state Markov process such that $\epsilon_\eta < 0$ conditional on being in the bottom two states of aggregate income, $\epsilon_\eta > 0$ conditional on being in the top two states of 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 (13).

E Simulations of the Benchmark Economy

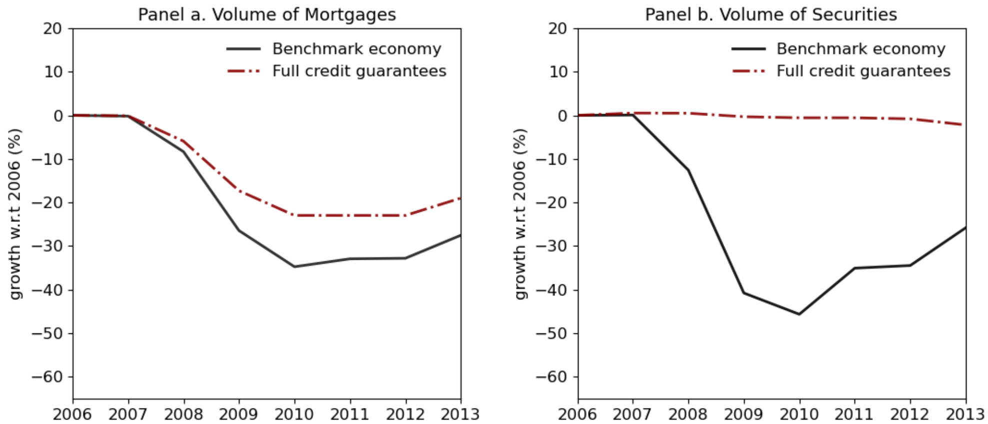
E.1 Application to the Great Financial Crisis. Additional variables

Figure 12: Households Aggregates during the Great Financial Crises



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

Figure 13: Economies with full and partial credit guarantee



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

E.2 Welfare analysis

Table 8: Welfare Changes in Consumption Equivalent Units

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

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

F Quantifying Information Frictions

In this section, we design a comparable complete information economy featuring similar distortions and government policies as the asymmetric information one. Then, we use this alternative economy as a benchmark to measure the role of information frictions in amplifying the effects of income and housing shocks.[42]

[42] In Section **??**, we showed that in a complete information economy, the securitization market does not experience adverse selection, and there is no need for credit guarantees or charging origination fees on lenders.

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.[43] Such a wedge is represented by the area between equilibrium cut-offs $\{z^S, z^B\}$ in Figure **??**. 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:

$$\begin{aligned} V(b, z; X) &= \max_{\{c,n,b',d,s_h,s_\ell\}} \left[u(c) + \beta^L \mathbb{E}_{X'} V(b', z', X')|X\right] \\ s.t. & \\ c + n(zq+\gamma) + pd(1-\tau)\varphi &\leq ((1-x_\ell)b - s_h)\, m_h + x_\ell b m_\ell + p s_h + d_t m_d \varphi - T^L b + T^{\varphi} b \\ b' &= (1-\phi)\left((1-x_\ell)b - s_h + x_\ell b(1-\rho) + d\right) + n \\ & n \geq 0 \quad d \geq 0 \\ & s_h \in [0, (1-x_\ell b] \end{aligned} \tag{26}$$

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

Equivalence with an asymmetric information economy. The recursive problem of a lender in a complete information economy facing the wedge $\varphi_t \equiv \frac{1}{1-\mu_t}$ is equivalent to the problem it faces in the asymmetric information economy presented in (16). Start by conjecturing that prices $\{p_t, q_t\}$ coincide in the asymmetric-information economy and the complete information economy with the information-wedge. Since government policy is kept

Such an economy may not serve as an appropriate counterpart to study the role of information frictions since it overlooks distortions in lenders' decisions introduced by government policy.

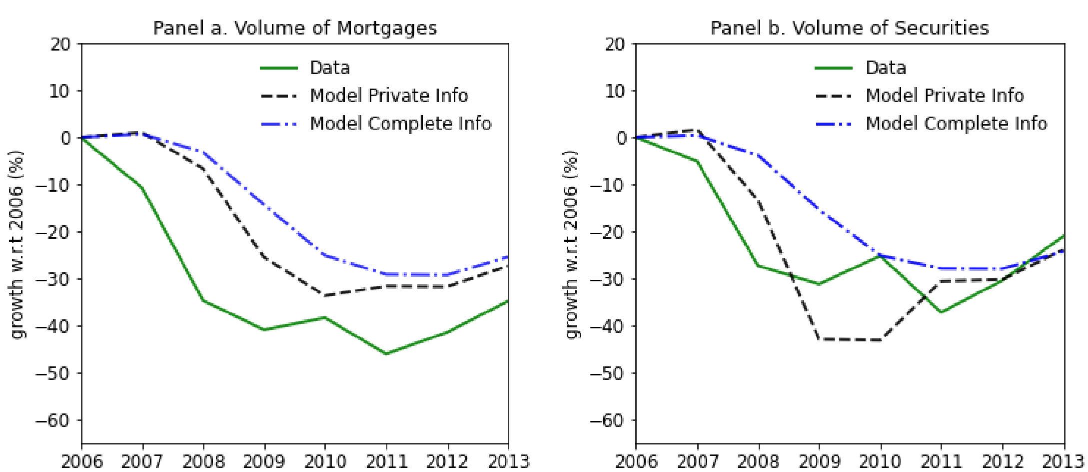
[43] The idea of mapping economic frictions to wedges was developed by Chari et al. (2007) to study business cycle fluctuations in a prototype growth model. Kurlat (2013) adapts the same idea to map information frictions in a model of asset creation and reallocation.

fixed in both economies, 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 in both economies. Furthermore, whenever the information-wedge $\varphi = \frac{1}{1-\mu_t^*}$ where μ_t^* is the equilibrium value of the asymmetric information economy, the second equilibrium cut-off of both economies also coincides. Thus, the level of distortions faced by both economies in the securitization market is the same.

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

First, we simulate the benchmark economy with information frictions for $T = 100,000$ periods. Then, using the simulated allocations and prices, we compute the average information friction wedge $\bar{\varphi} = \sum_{t=1}^{T} \frac{1}{T}\varphi_t$, and the average value of the guarantee policy $\bar{\tau} = \sum_{t=1}^{T} \frac{1}{T}\tau_t$. These estimates are introduced in the comparable complete information economy so that it faces, on average, similar distortions over time. It is important to note that the comparable complete information economy shares the exact calibration as the benchmark economy with information frictions. Then, we simulate both economies for the identical sequences of income and housing volatility shocks presented in Figure 10. Figure 14 shows the dynamic responses of aggregate credit and securitization volumes from each economy compared to their data counterparts.

Figure 14: Quantifying Information Frictions During the Great Financial Crisis



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

Table 9: Model predicted average contraction (pp), 2008-13

Aggregates	Private Information	Complete Information	Data
Volume of Mortgages	-28.2	-22.9	-40.6
Volume of Securities	-32.5	-22.5	-29.8

Table 9 summarizes the average contraction predicted by each economy for aggregate credit and securitization volumes for the period 2008 to 2013. On average, the benchmark economy with private information fits the data better than the comparable complete information economy. We estimate that information frictions multiplier of 1.2 for the credit contraction and a multiplier of 1.4 for the contraction in security issuance during the GFC. These multipliers rise as the probability that a lender privately identifies non-performing low-quality loans increases. For instance, an economy where lenders can perfectly identify all low-quality loans that will fail to perform can be replicated by setting $\rho = 1$ in our benchmark economy. Such an environment generates larger amplification effects from information frictions; repeating the above exercise yields multipliers of 1.3 for the credit contraction and 1.7 for the securities contraction during the GFC.

G Proofs to Lemmas and Propositions

G.1 Derivation of borrowers default threshold

The recursive representation of the representative borrower household problem (20) 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. The aggregate household default rate is defined as:

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

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

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

also, notice that

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

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

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

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

By the Envelope Theorem:

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

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

$$
q = \tilde{\xi} + \beta^B \mathbb{E}\left[\frac{U'_c}{U_c}(1 - \lambda(\bar{\omega}'))(q'(1-\phi') + m')\right] \tag{27}
$$

$$
p^H(1 + \Xi_{H'} - \pi\tilde{\xi}) = \beta^B \mathbb{E}\left[\frac{U'_c}{U_c}\left((1 - \lambda(\bar{\omega}'))\mu_\omega(\bar{\omega}')p^{H'} + \frac{U'_H}{U'_C}\right)\right] \tag{28}
$$

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

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

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

$$
\begin{aligned}
U_c(-\bar{\omega} g_\omega(\bar{\omega})p^H H + g_\omega(\bar{\omega}) m B) + \tilde{\xi}(1-\phi) g_\omega(\bar{\omega}) B &= -\beta^B \mathbb{E}\left[\frac{\partial V}{\partial B'}\frac{\partial B'}{\partial \bar{\omega}}\right] \\
U_c g_\omega(\bar{\omega})(-\bar{\omega} p^H H + mB) + U_c \tilde{\xi}(1-\phi) g_\omega(\bar{\omega}) B &= \beta^B \mathbb{E}\left[\frac{\partial V}{\partial B'}(1-\phi) g_\omega(\bar{\omega}) B\right] \\
U_c g_\omega(\bar{\omega})(-\bar{\omega} p^H H + mB + \tilde{\xi}(1-\phi)B) &= (1-\phi) g_\omega(\bar{\omega}) B \left[\beta^B \mathbb{E}[V_{B'}]\right] \\
U_c g_\omega(\bar{\omega})(-\bar{\omega} p^H H + mB + \tilde{\xi}(1-\phi)B) &= -(1-\phi) g_\omega(\bar{\omega}_h) B U_c (q - \tilde{\xi}) \\
\bar{\omega} &= \frac{B}{p^H H}[m + (1-\phi)q]
\end{aligned} \tag{29}
$$

G.2 Proof of Lemma 1

1. Assumptions: (i) lender holds one asset: budget set is linear in b, and (ii) homothetic preferences, $u(c) = \log(c)$, imply that policy functions are linear in b.

2. Lender's idiosyncratic origination costs are assumed identical and independently distributed across lenders and across time.[44] Independence across lenders implies that the joint distribution of debt holdings and idiosyncratic shocks $\Gamma(b, z)$ at time t can be integrated using their respective CDFs. $\Gamma(z, b) = F(z)G(b)$, where $G(b)$ represents the CDF for the stock of loan holdings at any given period. Also, independence across time implies that these shocks do not correlate with aggregate shocks.

3. For given $\{p, q, \mu\}$: aggregates $\{S_h, S_\ell, D\}$ do not depend on the distribution of b. Therefore, neither do market clearing values $\{p,\ q,\ \mu\}$. See additional derivations G.11.

4. Thus, it is not necessary to know the joint distribution Γ to compute aggregate quantities and prices. B is a sufficient statistic.

G.3 Proof of Lemma 2

1. Taking portfolio lending decisions b' as given, the problem of a lender in (16), consists of maximizing dividends c by choosing $\{n, s_h, s_\ell, d\}$, which implies solving a linear problem. To see this, combine a lender's budget constraint (13) and the portfolio's law of motion (12), which yields

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

$$s.t.$$

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

[44] An interesting avenue for future research is to study a more general setup where a lender's origination cost z_t^j features partial persistence, this would generate correlation between portfolio holdings and origination costs.

Each lender takes prices as given, $\{p, q, \mu\}$. Trading decisions are derived by comparing static payoffs. For sales of low-quality loans s_ℓ: Whenever $p > m_\ell + (zq+\gamma)(1-\phi)(1-\rho)$, a lender with draw z has no incentive to keep a low-quality loan. Let the condition for low-quality loans sales be $p > m_\ell + \Theta$, where $\Theta \equiv (\bar{z}q + \gamma)(1-\phi)(1-\rho)$. Then, for any z a lender chooses to sell all their low-quality loans, hitting the corner in (15): $s_\ell = x_\ell b$. The decision to sell high-quality loans s_h is based on how a internal valuation of their loans, given by $m_h + (zq+\gamma)(1-\phi)$, compares to the price of selling them. Taking into account the portfolio constraint in (14) 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.

2. Given a lender's draw of origination cost $z \in [\underline{z}, \bar{z}]$, her trading decisions can be characterized according to cutoffs $\{z^S, z^B\}$.[45] We define 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 (12) 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 (12) obtains policy functions for $d = \frac{b' - (1-x_\ell)(1-\phi)b}{(1-\mu)(1-\phi)}$ and $n = 0$.
    - Holder. A lender with $z \in \left[z^S,\ z^B\right]$ and $\{d = 0,\ s_h = 0,\ s_\ell = x_\ell b\}$. Replacing these decisions in (12) obtains $n = b' - (1-x_\ell)(1-\phi)b$, with $n \geq 0$.

3. If there is no positive price that clears supply and demand, the securitization market will not be active. The quality distinction within a lender's portfolio becomes irrelevant. Trading decisions for all lenders are trivial: $\{d = 0,\ s_h = 0,\ s_\ell = 0\}$. Replacing these

[45] These equilibrium cut-offs are well defined in the support $[\underline{z}, \bar{z}]$. Also, the fraction of non-performing 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.

decisions in (12) obtains the origination decision: $n = b' - (1-\lambda(\bar{\omega}))(1-\phi)b \geq 0$ given that $\rho x_\ell = \lambda(\bar{\omega})$.

G.4 Proof of Lemma 3

The first part of this proof defines a lender's generic wealth function that represents a convex version of a lender's original budget set (13). The second part derives the consumption-lending rule.

1. A lender's virtual wealth function is defined as

$$W(b,z,X) = b\left[x_\ell p + (1-x_\ell)\max\{p,(1-\phi)\min\left\{zq+\gamma,\ \frac{p(1-\tau)-m_d}{(1-\mu)(1-\phi)} + m_h\right\} - T^L\right]. \quad (30)$$

   The virtual wealth represents a lender's consolidated wealth as a generic function of her origination cost z, prices $\{q,p,\mu\}$, and lending and trading decisions $\{n,d,s_h,s_\ell\}$. It consolidates the lender's sources of income: cash payments from her maturing portfolio, cash from selling loans, and the virtual valuation of her stock of loans—at either the market price or at the lender's internal valuation rate. Using (30) we can define a convex budget set that is weakly larger than the original budget set in problem (16). The problem of a lender under this relaxed budget set is given by

$$\begin{aligned} V(b,z;X) &= \max_{\{c,b'\}} \log(c) + \beta^L \mathbb{E}_{X'|X} V(b',z';X') \qquad (31) \\ s.t. & \\ & c + b'\min\left\{zq+\gamma,\frac{p(1-\tau)-m_d}{(1-\mu)(1-\phi)}\right\} \leq W(b,z;X). \end{aligned}$$

2. Policy functions $\{c,b'\}$ are derived by guess and verify. First Order Conditions w.r.t b':

$$\begin{aligned} \frac{1}{c}\min\left\{zq+\gamma,\frac{p(1-\tau)-m_d}{(1-\mu)(1-\phi)}\right\} &= \beta^L \mathbb{E}_{X'|X}\left[V_{b'}(b',z';X')\right] \\ &= \beta^L \mathbb{E}_{X'|X}\left[\frac{1}{c'}W_{b'}(b',z';X')\right] \end{aligned}$$

   where the second equation holds because of the Envelope theorem, and $W_b = \frac{\partial W(b,z;X)}{\partial b}$ is the marginal change in a lender's virtual wealth from increasing the stock of loans in one unit. Next, guess that the policy function for consumption has the form: $c =$

$\varrho W(b,z;X)$, where $\varrho \in (0,1)$. Then, from budget set in (31):

$$\begin{aligned} b' &= \frac{(1-\varrho)W(b,z;X)}{\min\left\{zq+\gamma, \frac{p(1-\tau)-m_d}{(1-\mu)(1-\phi)}\right\}}, \\ c' &= \varrho W(b',z';X') \\ &= \varrho W_{b'}(b',z';X')b' \\ &= \varrho W_{b'}(b',z';X')\left[\frac{(1-\varrho)W(b,z;X)}{\min\left\{zq+\gamma, \frac{p(1-\tau)-m_d}{(1-\mu)(1-\phi)}\right\}}\right]. \end{aligned}$$

Replacing expression for c' in the Euler equation obtains:

$$\begin{aligned} \frac{1}{c}\min\left\{zq+\gamma, \frac{p(1-\tau)-m_d}{(1-\mu)(1-\phi)}\right\} &= \beta^L \mathbb{E}_{X'|X}\left[\frac{\min\left\{zq+\gamma, \frac{p(1-\tau)-m_d}{(1-\mu)(1-\phi)}\right\} W_{b'}(b',z';X')}{\varrho W_{b'}(b',z';X')\left[(1-\varrho)W(b,z;X)\right]}\right] \\ \frac{1}{\varrho W(b,z;X)} &= \beta^L \mathbb{E}_{X'|X}\left[\frac{1}{\varrho(1-\varrho)W(b,z;X)}\right] \\ \varrho &= 1-\beta^L, \end{aligned}$$

which yields policy functions: $c = (1-\beta^L)W(b,z;X)$ and

$$b' = \frac{\beta^L}{\min\left\{zq+\gamma, \frac{p(1-\tau)-m_d}{(1-\mu)(1-\phi)}\right\}} W(b,z;X).$$

For the second part, suppose there are lenders for whom the solutions of each program differ. Such lenders must be a buyer or a holder, since both programs are identical for sellers. Then, at least one buyer or holder chooses $b' < (1-x_\ell)(1-\phi)b$ but given the non-negativity constraint on purchases, it must be that such buyer purchases $d = 0$. By revealed preferences, if every buyer chooses to buy zero then aggregate demand $D = 0$.

G.5 Proof of Lemma 4

Whenever $p > m_\ell + \Theta$ the securitization market clears, by Lemma 2 the policy function of holder-lenders implies a strictly positive amount of new loan issuance.[46] Hence, the last marginal lender to originate loans is such that $z \leq z^B$. Instead, whenever the securitization market is inactive, the virtual wealth function of the lender becomes $W =$

[46]The case: $0 < p < m_\ell$, would imply that lenders prefer to keep low-quality loans instead of selling them. We ruled out this case, as it would yield counterfactually low prices for securities in any data-consistent calibration of the foreclosure recovery function; see the Calibration section.

$b\left[(1-\lambda(\bar{\omega}))m+\lambda(\bar{\omega})\Psi+(1-\lambda(\bar{\omega}))(1-\phi)zq\right]$ which acknowledges that $\rho x_\ell=\lambda(\bar{\omega})$. Using the policy functions for b' in Lemma 3, new loans become $n = \Big[\frac{\beta^L}{zq}((1-\lambda(\bar{\omega}))m+\lambda(\bar{\omega})\Psi)-(1-\beta^L)(1-\lambda($
Then, the upper bound for z so that a lender issues a strictly positive amount of new loans is:

$$\hat{z} \equiv \min\left\{\bar{z}, \frac{\beta^L}{(1-\beta^L)}\frac{m+\frac{\lambda}{1-\lambda}\Psi}{q(1-\phi)}\right\} > z$$

the left hand side determines $\hat{z}$ when securitization market is not active. Lastly, this upper bound is relevant as long as it is within the support of the origination costs drawn by lenders, the min function incorporates that.

G.6 Proof of Lemma 5

First, given that G'_ω is a mean preserving spread of G_ω by definition it satisfies: $G_\omega(\omega) \leq G'_\omega(\omega)\ \forall\ \omega$ in the support. Second, in steady state, borrowers default is function given by $\lambda(\bar{\omega}) = G_\omega(\bar{\omega})$ where $\bar{\omega}$ is given by (29). Then, ceteris paribus, an increase in the housing volatility implies that: $\lambda(\bar{\omega}) \leq \lambda'(\bar{\omega})$.

G.7 Proof of Lemma 6

Lemma 6 establishes that the fraction of securitized non-performing loans μ is increasing in borrowers default rate $\lambda(\bar{\omega})$ and decreasing in the securitization market cut-off $\tilde{z}^S$. For the sake exposition, we assume an economy in steady state with $\rho = 1$ and $\psi = 0$ so we abstract from the recovery from foreclosure channel and focus on the dynamics arising from household default.

1. by definition

$$\begin{aligned}\mu(\lambda,\tilde{z}^S) &= \frac{S_\ell}{S(\tilde{z}^S)}\\ &= \frac{\int \lambda(\bar{\omega})b\ d\Gamma(z,b)}{S_\ell(\tilde{z}^S)+S_h(\tilde{z}^S)}\\ &= \frac{\lambda(\bar{\omega})}{\lambda(\bar{\omega})+(1-\lambda(\bar{\omega}))F(\tilde{z}^S)}\end{aligned}$$

   where F is the CDF of z.

2. for a given cut-off $\tilde{z}^S$, consider an increase in the default rate arising from higher housing volatility. In Lemma 6 we established that such increase in volatility implies:

$\lambda(\bar{\omega}) \leq \lambda'(\bar{\omega})$. Then, we want to show that:

$$\begin{aligned}
\mu(\lambda', \tilde{z}^S) &\geq \mu(\lambda, \tilde{z}^S) \\
\frac{\lambda'(\bar{\omega})}{\lambda'(\bar{\omega}) + (1-\lambda'(\bar{\omega}))F(\tilde{z}^S)} &\geq \frac{\lambda(\bar{\omega})}{\lambda(\bar{\omega}) + (1-\lambda(\bar{\omega}))F(\tilde{z}^S)} \\
1 + \frac{1-\lambda(\bar{\omega})}{\lambda(\bar{\omega})}F(\tilde{z}^S) &\geq 1 + \frac{1-\lambda'(\bar{\omega})}{\lambda'(\bar{\omega})}F(\tilde{z}^S) \\
\frac{\lambda'(\bar{\omega})}{\lambda(\bar{\omega})}\frac{(1-\lambda(\bar{\omega}))}{(1-\lambda'(\bar{\omega}))} &\geq 1
\end{aligned}$$

which is satisfied.

3. keeping the default rate fixed, consider $\tilde{z}^{S\prime} > \tilde{z}^S$, then given that the CDF is a strictly increasing function $F(\tilde{z}^{S\prime}) > F(\tilde{z}^S)$. Then, following the same as strategy as before, it is straightforward to see that $\mu(\lambda, \tilde{z}^{S\prime}) \leq \mu(\lambda, \tilde{z}^S)$.

A corollary of Lemma 6 is that under an appropriate assumption on the density of lender's costs distribution $F(z)$, we can guarantee that the z^B cutoff moves in the opposite direction to the z^S cutoff whenever the economy experiences a shock that increases household default rates.

G.8 Proof of Proposition 1

The proof consists in showing that the implied discount price of new mortgage debt satisfied the relation presented in Proposition 1. First, we derive the analytical expression for each discounted price and then verify the inequality. In steady state, the household demand for new credit is given by

$$N^D_{ss} = B_{ss}(1 - (1-\phi)(1-\lambda(\bar{\omega})))$$

In a complete information economy, low-quality loans are not traded since all lenders can easily identify them. Without loss of generality, we assume that ρ equals one and ψ equals zero. When the securitization market is active, lenders' consumption, lending, and trading decisions can be derived in a similar fashion to Lemma 2. In this case, there is only one cutoff $z^{CI} \equiv \frac{p-m}{q}$. All lenders self-classify into two groups: sellers and buyers. In the aggregate, the total supply of new loans is given by integrating the supply of new loans from sellers:

$$\begin{aligned}
N^S_{ss} &= \int_{\underline{z}}^{z^{CI}} n^{CI}(b, z; X) d\Gamma(b, z) \\
&= B_{ss}\frac{\beta^L}{q^{CI}}\left((1-\lambda(\bar{\omega}))p^{CI}\right)\int_{\underline{z}}^{z^{CI}} \frac{1}{z} dFz
\end{aligned}$$

Notice that aggregate supply is a function of the discounted price of debt. Then, using the market clearing condition $N_{ss}^D = N_{ss}^S$ we can derive an expression for the discounted price of new mortgage debt in steady state:

$$q_{ss}^{CI} \quad = \quad \frac{\beta^L(1-\lambda(\bar{\omega}))p^{CI}\int_{\underline{z}}^{z^{CI}}\frac{1}{z}dFz}{1-(1-\lambda(\bar{\omega}))(1-\phi)} \tag{32}$$

When the securitization market is inactive (NSM), lenders' decisions can also be derived directly from Lemma 2. In steady state the aggregate credit supply is given by:

$$\begin{aligned}
N_{ss}^{NSM} &= \int_{\underline{z}}^{\bar{z}} n^{NSM}(b,z;X)d\Gamma(b,z) \\
&= \int_{\underline{z}}^{\bar{z}} b'^{NSM} - (1-\lambda(\tilde{\omega}))(1-\phi)b \; d\Gamma(b,z) \\
&= B_{ss}\frac{1}{q^{NSM}}\beta^L(1-\lambda(\tilde{\omega})m)\int_{\underline{z}}^{\bar{z}}\frac{1}{z}dFz - B_{ss}(1-\beta^L)(1-\phi)(1-\lambda(\tilde{\omega}))
\end{aligned}$$

w.l.o.g we assume $\bar{z} \geq \hat{z}$ from Lemma 4. Then, using the market clearing condition for the credit market, obtains an expression for the discounted price of new mortgage debt in the steady state:

$$q_{ss}^{NSM} \quad = \quad \frac{\beta^L(1-\lambda(\tilde{\omega}))m\int_{\underline{z}}^{\bar{z}}\frac{1}{z}dFz}{1-\beta^L(1-\lambda(\tilde{\omega}))(1-\phi)} \tag{33}$$

The last step consists in comparing equations (32) and (33). Notice that $p^{CI} > m$ and for any $z^{CI} \in [\underline{z}, \bar{z})$ the numerators satisfy

$$\int_{\underline{z}}^{z^{CI}}\frac{1}{z}dFz > \int_{\underline{z}}^{\bar{z}}\frac{1}{z}dFz \quad \forall\ z^{CI} < \bar{z}.$$

G.9 Proof of Proposition 2

First, show that an economy with a full credit guarantee has lower intermediation cost compared to an economy with partial credit guarantee. W.l.o.g we assume that ρ equals one. Note that the distance between the equilibrium cutoff functions in an economy with asymmetries of information is given by

$$z^B(AI) - z^S(AI) = \frac{1}{q(1-\phi)}\left[\frac{p(1-\tau)-m_d}{(1-\mu)} - (p-m_h)\right]$$

whenever $\tau = \mu$ the distance is minimized: $z^B(AI) - z^S(AI) = \frac{1}{q(1-\phi)}(m_h - \frac{m_d}{1-\mu})$, which implies that the set of holder-lenders shrinks to its minimum, and the sets of sellers and buyers expand. This reduces intermediation costs and brings the economy closer to the complete information case where there is only one equilibrium cutoff, hence, improving allocative efficiency.

Second, we show that the aggregate demand of securities in a full subsidy economy with private information is always larger than the aggregate demand of securities in a complete information economy. We begin by deriving the aggregate demand of securities in each case. For the complete information economy in steady state, given equilibrium market prices $\{p^{CI}, q^{CI}\}$:

$$\begin{aligned} D^{CI} &= \int d^{CI}(b, z; X)\ d\Gamma(b, z) \\ &= \left(1 - F\left(z^{CI}\right)\right) B_{ss} \left[\frac{\beta^L}{p^{CI} - m}((1-\lambda^{CI})p + \lambda^{CI}\Psi) - (1-\beta^L)(1-\lambda^{CI})\right] \end{aligned}$$

For an economy with private information with a full subsidy (FS) policy ($\tau = \mu$), given steady state market prices $\{p^{FS}, q^{FS}\}$:

$$\begin{aligned} D^{FS} &= \int d^{FS}(b, z; X)\ d\Gamma(b, z) \\ &= \frac{1 - F\left(z^{FS}\right)}{1-\mu} B_{ss} \left[\frac{\beta^L}{p^{FS} - \frac{m}{1-\mu}}((1-\lambda^{FS})m + \lambda p^{FS} - T^L) - (1-\beta^L)(1-\lambda^{FS})\right] \end{aligned}$$

Notice that between an economy with private information and an economy with complete information, cutoffs satisfy: $z^{AI} \leq z^{CI}$, this follows from the positive wedge associated to private information that reduces the mass of sellers and buyers in the securitization market (Lemma 2). Since a full subsidy economy is a special case of the private information setup with no wedge, cutoffs also satisfy $z^{FS} \leq z^{CI}$. Then, it follows that the mass of buyers satisfies $1 - F\left(z^{FS}\right) \geq 1 - F\left(z^{CI}\right)$. Also, notice that $1/(1-\mu) > 1$ as the fraction of securitized non-performing loans is always strictly positive even with a full subsidy. Without loss of generality, we assume the steady state amount of debt is the same in both economies. We check that the expression in the square bracket from D^{FS} is larger than its counterpart in D^{CI} for a large range of the parameters given by the calibration in section 4, as the first term is substantially larger than the rest.

The condition for a market crash is derived from the aggregate demand of securities, see

Subsection G.11. In steady state we have:

$$\begin{aligned} D &= \int d(b,z;X)\ d\Gamma(b,z) \\ &= \int_{z^B}^{\bar{z}} \frac{b' - (1-\lambda)(1-\phi)b}{(1-\mu)(1-\phi)}\ d\Gamma(b,z) \\ &= \frac{1-F(z^B)}{1-\mu} B \left[\frac{\beta^L(1-\mu)}{p(1-\tau)-m}((1-\lambda(\bar{\omega}))m - T^L) - (1-\beta^L)(1-\lambda(\bar{\omega}))\right] \\ &\quad + \frac{\beta}{p(1-\tau)-m} B \underbrace{(1-F(z^B))\lambda(\bar{\omega})p}_{S_\ell^{\text{buyers}}} \end{aligned}$$

where S_ℓ^{buyers} denotes the supply of low-quality loans from lenders that buy securities. Notice that if $D < S_\ell^{\text{buyers}}$ then there cannot be a positive price clearing the securities market. Rearranging the expression in the large bracket yields a sufficient condition for the securities market not to be active:

$$\min_p \left\{ p \frac{(1-\tau)-m}{(1-\mu)} \right\} > \frac{\beta^L m}{(1-\beta^L)(1-\lambda)}$$

Item 1 follows directly as aggregate demand for securities becomes zero when the above condition is satisfied. Item 2 follows from Lemma 2 for the case in which the securitization market is inactive. Item 3 follows from Proposition 1.

G.10 Proof of Proposition 3

First, in Lemma 5 we established that an exogenous increase in the volatility of housing valuation shocks that preserves the mean of the distribution will lead to an increase in borrowers' default rate. Then, whenever Lemma 6 is satisfied, item 1 follows. Second, by the corollary in Lemma 6 the second cutoff will increase when the fraction of securitized non-performing loans increases. By the definition of the aggregate demand of securities (**??**), implies that the mass of buyers will decrease. Consequently, the quantities of securities demanded will also decrease because lenders who still buy securities have limited funds (cash) and cannot borrow from external sources. Third, lower demand and supply push the market price of securities down, which necessarily settles a lower price than before for supply and demand to clear.

G.11 Additional derivations

For Proof of Lemma 1

1. Given that $z \sim i.i.d.$, and the linearity of policy functions on b, the aggregate supply and demand of securities $\{S, D\}$ do not depend on the joint distribution $\Gamma(b, z) = F(z)G(b)$, where $F(z)$ and $G(b)$ are the respective CDFs. Working out the expressions for supply and demand in the securitization market from the definitions obtains:

   (a) Aggregate Supply of loans, S

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

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

2. 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.

   (a) 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:

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

(b) 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.

$$N^L = \int n(b, z; X) d\Gamma(b, z)$$

There are two possible expressions for the aggregate supply of credit. The first case when the securitization market is active,

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

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

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

Budget sets by lender type

Replacing the optimal origination and trading decisions of Lemma 2 in the budget constraint and in the law of motion of lenders, problem (16), 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:

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