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Abstract

I develop a macro 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 interest rates for borrowers. 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 expansion and contractions of mortgage credit through the securitization liquidity channel. Adverse selection generates a multiplier effect of household shocks. Applying the theory to the Great Financial Crisis, I quantify that information frictions amplified the observed mortgage credit contraction by a factor of 1.5. The multiplier is an endogenous function of the severity of information frictions. A subsidy policy in the securitization market can stabilize liquidity and credit cycles. However, the policy generates inefficiently high liquidity and fails to realize meaningful welfare gains for households.

Keywords: securitization, banking, DSGE, private information, liquidity frictions.

JEL classification: D5, D82, G21, G28.

Resumen

Este trabajo desarrolla un modelo macroecómico del sistema financiero inmobiliario de Estados Unidos. El modelo conecta las dinámicas del mercado de crédito hipotecario y las del mercado de titularización de bonos hipotecarios en equilibrio general. La titularización hipotecaria emerge de manera endógena como una tecnología eficiente para transferir activos ilíquidos entre agentes y canalizar mayor liquidez hacia la provisión de crédito hipotecario, reduciendo de esta manera costos de intermediación y los tipos de interés hipotecarios. Sin embargo, estos beneficios se ven disminuidos por la información privada que poseen los bancos emisores de hipotecas sobre la probabilidad de impago de los hogares prestatarios, lo que genera un problema de selección adversa en el mercado de titularización hipotecaria. En el modelo, fluctuaciones en el riesgo crediticio de los hogares conllevan fluctuaciones en la provisión de crédito hipotecario a través del canal de liquidez de titularización. El problema de selección adversa genera un efecto multiplicador que amplifica los choques financieros que experimentan los hogares. Como aplicación, el presente trabajo cuantifica que las fricciones de información multiplicaron 1,5 veces la contracción de crédito observada durante la Gran Crisis Financiera en el mercado hipotecario estadounidense. Una política de subsidios en el mercado de titularización puede estabilizar la liquidez y los ciclos de crédito hipotecario. Sin embargo, esta política genera niveles ineficientemente altos de liquidez y pequeñas ganancias de bienestar a los hogares.

Palabras clave: titularización, hipotecas, bancos, información privada, equilibrio general.

Códigos JEL: D5, D82, G21, G28.

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.[1] 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 macroeconomics variable and a policymaker objective in the U.S.[2] During the last decade, extensive empirical 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.[3] Yet, we have less understanding about the role of information frictions in accounting for aggregate credit dynamics, and several key questions remain unanswered: Do information frictions amplify mortgage credit responses to household shocks? What is the channel of transmission of shocks from the securitization market to the credit market? What is the role of policy in this environment?

In this paper, I tackle these questions by developing a theory that delivers an equilibrium connection between the securitization market and the mortgage credit market. 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 further leads to sharp declines in security issuance and mortgage credit to households. Hence, adverse selection generates a multiplier effect of households' shocks in the mortgage market's aggregates. A quantification of this adverse selection multiplier shows that it could have amplified the mortgage credit contraction by a factor of 1.5, during the Great Financial Crisis (GFC). The model's success in generating large fluctuations in both markets rests on two forces: (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.

[1]According to statistics from the Home Mortgage Disclosure Act (HMDA) database. See Feng et al. (2021). Also, see Section 2 for a summary of U.S. mortgage trends during the last two decades.

[2]The U.S. government, through the government-sponsored enterprises Freddie Mac and Fannie Mae, has the explicit objective of supporting a stable source of liquidity to provide mortgage credit to households.

[3]Adelino et al. (2019), 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 to the detriment of buyers, giving rise to an adverse selection problem. On theoretical grounds, building on the insights of Akerlof (1970), the economics profession has developed models of dynamic adverse selection (see Eisfeldt (2004), 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.

The theory builds on a standard dynamic stochastic general equilibrium model of financial intermediation used in the macro literature of housing. Impatient borrower households, facing aggregate income and housing risk, take on long-term mortgages to finance their purchases of housing services and non-durable goods. 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, I extend this standard setup along several key dimensions. First, borrower households can endogenously default on their mortgages, which defines the quality of loans that lenders hold. Second, lenders face heterogeneous loan origination costs, which capture the differences in loan origination technologies 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 loans in their portfolios. Fourth, there is a securitization market where lenders can sell loans and buy securities.

The securitization process relies on pooling many loans of heterogeneous qualities to form securities. It captures the structure 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, my 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. Hence, I further the theory 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 interest rate on mortgage credit 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, the household's default rate, and lenders' trading decisions.

The government's involvement in the securitization market is captured by a subsidy 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 to households. The subsidy captures the role of the credit guarantees provided by government-sponsored entities (GSEs) to buyers of MBS.[4] 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.

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 borrower households to default on their mortgages, 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 an adverse selection problem. 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; hence, securities trade at a discount. In times of low default risk, the liquidity value and the cost-sharing benefits of securitization generally

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

exceed the adverse selection discount implied by asymmetric information. Information asymmetry is exacerbated by the increase in households' credit risk. Buyers face a higher discount, demand for securities falls, and securities trade at a lower price. In the credit market, lenders face an endogenous liquidity shortage derived from the unwillingness to securitize their portfolios at current 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.

A collapse in the securitization market can endogenously occur in equilibrium when information frictions become too severe. In such episodes, the credit market still operates, but it does so with a price adjustment, which leads to a higher mortgage rate, lower credit intermediation, and lower aggregate consumption of housing and final goods. These patterns closely replicate the dynamics observed in the U.S. market.

A quantitative test of the model shows that it can successfully replicate the dynamics observed in the data. The baseline model is calibrated to match key moments of the cross section and time series of the U.S. mortgage market before the GFC. In the data, mortgage credit contracted by 40 percent and MBS issuance contracted by 36 percent on average from 2008 to 2013. When households in the baseline model are hit by the same sequence of income and housing valuation shocks observed in the data during this period, the model successfully replicates two-thirds of the contraction in mortgage credit and the full contraction in MBS issuance. A decomposition of the underlying forces shows that information frictions amplified the credit contraction by a factor of 1.5. In other words, in the absence of information frictions, aggregate mortgage credit would have contracted by 27 percent instead of 40 percent. The decomposition also shows that housing valuation shocks account for about half of the dynamics, and household income shocks account for about 5 percent.

The transmission of fluctuations from the securitization market to the credit market depends on the cross-sectional distribution of credit lending across lenders. I use granular data from the HMDA database to discipline the distribution of lending in the model. These cross-sectional moments inform the model about the magnitude of amplification that the adverse selection multiplier can generate in equilibrium.[5] Given such market structure, contractions in the volume of security issuance generate large contractions in the volume of credit when some of the large originators are unable to securitize their portfolios.

The securitization market experienced several structural changes—as well as policy changes– after the GFC. The expansion of the market share of GSEs marked a structural change, which, starting from 2009, has accounted for close to the entire MBS market. Second, starting in 2012, the credit guarantee fee charged by GSEs to mortgage originators increased threefold. A quantitative assessment of the post-GFC economy yields a more stable mortgage market. The volatility of quantities and prices in the credit and securitization markets declines, along with a decline in the probability of a securitization collapse. However, the policy generates inefficiently high levels of

[5]A distinctive feature of the distribution of mortgage lending is the high level of concentration among originators. Mortgage lending is concentrated among a few large originators: 10 percent of originators account for 90 percent of all new loan issuance to households in the residential mortgage market.

liquidity and fails to realize high welfare gains for households. Households face higher interest rates as lenders pass through part of the guarantee fee and pay higher taxes since financing this policy requires higher tax pressure. These insights complement existing studies of the GSE's credit guarantee policy from a general equilibrium perspective.

Related Literature. My work fits within the strand of literature that introduces financial and information 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)). I contribute to this literature by quantifying the role of information and liquidity frictions in accounting for the joint dynamics of mortgage credit and MBS issuance during the GFC. 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). My model provides a microfoundation for Justiniano et al. (2019)'s lending constraints by modeling the dynamics of securitization as a major source of liquidity to mortgage lenders. Landvoigt (2016) also introduces securitization in a DSGE model in a reduced form. My 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 dynamics for the availability of credit in the U.S. mortgage market since the 2000s.[6]

My framework emphasizes the role of information frictions and its interplay with liquidity frictions in amplifying credit cycles. 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.[7] Shimer (2014) performs a comprehensive review of the studies measuring private information in the MBS market along several dimensions and how the market deals with it. On theoretical grounds, I build on extensive work that studies adverse selection in financial markets, a tradition that dates back to Akerlof (1970). My framework for modeling adverse selection in asset markets applies and extends the work of Kurlat (2013) to capture specific features of the TBA forward market for MBS and also shares elements present in Eisfeldt (2004), Bigio (2015), Vanasco (2017), Caramp (2019), Neuhann (2019), and Asriyan (2020). These papers show that adverse selection can generate large fluctuations in the volume of traded assets by ampli-

[6]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).

[7]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 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.

fying the effects of exogenous shocks in the economy.[8] My 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 the best of my knowledge, my paper is the first to quantify the aggregate effects of information asymmetries in the mortgage market through a securitization liquidity channel. Along this line, my 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 lending markets. 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. While these works focus on the relation between borrowers and lenders, my 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 model of the mortgage market. They find that underpriced mortgage guarantees, together with deposit insurance, encourage the banking sector to lever up excessively. I provide a complementary view of the effects of a mortgage guarantee policy. By modeling information frictions, my framework generates a meaningful role for a guarantee policy in the securitization market. A credit guarantee alleviates adverse selection problems by encouraging a stable demand for securities, which helps stabilize the flow of liquidity to mortgage lenders. Similar to Elenev et al. (2016), although for a different mechanism, I also find that credit guarantees were underpriced before the GFC. The actuarially fair price is closer to the one charged by GSEs after 2012.

Layout. The paper is structured as follows. Section 2 presents relevant features of the mortgage market that motivate the model in Section 3. Sections 4 and 5 present the theoretical and quantitatively analyses, and Section 6 concludes.

2 Motivating Observations

This section documents time series and cross-sectional patterns of the mortgage market as well as institutional features relevant to the theory developed in Section 3.[9]

[8] 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.

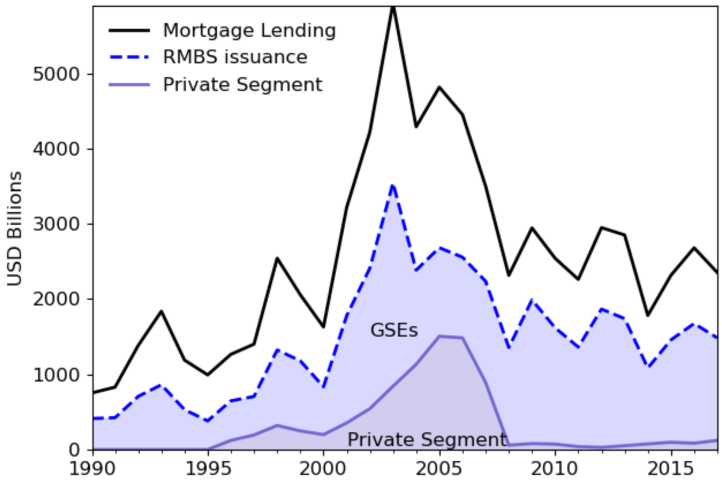
[9] This analysis is based on the Home Mortgage Disclosure Act (HMDA) database. See Appendix A for details about data treatment and the construction of variables.

2.1 The Credit and Securitization Markets

The mortgage market in the United States comprises two markets: a credit mortgage market, where mortgage originators issue mortgage loans to households, and a securitization market, where mortgages are sold, bundled, and transformed into mortgage-backed securities, a process known as securitization. The credit market links home buyers and mortgage originators, while the securitization market brings together mortgage originators and investors.[10]

Figure 1 shows how the volume of issuance of mortgage loans and the volume of issuance of residential mortgage backed securities (RMBS) move in tandem. This close connection is grounded in mortgage originators' reliance on securitization as a source of liquidity to fund new mortgages, instead of depending solely on deposits. The fraction of new loans sold, or securitized, in the securitization mortgage market during the first year of origination has steadily increased from around 50 percent in the 1990s to close to 80 percent in 2016, as shown in Figure 9 in Appendix B. During this period, on average, mortgage originators sold close to 70 percent of all mortgage loans within the first year of origination (see Table 1).

Figure 1: Credit and securitization mortgage markets



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

The high and positive correlation between both aggregates supports the idea of financially constrained mortgage originators. Expansions in demand for securities induce expansions of mortgage credit to households because originators can quickly securitize loans and free up resources to originate new ones. On the flip side, securitization market downturns represent a negative liquidity shock to originators; lower sales of mortgages and securities imply that originators must hold mortgages on their balance sheets for longer than expected, which can induce contractions in mortgage credit to households if banks do not hold enough capital or are unable to access other sources of funding.

[10]Most of these investors are financial institutions that manage large pools of savings, such as pension funds, mutual funds, insurance companies, and sponsors of structured products.

While securitization by private financial institutions collapsed abruptly in 2007 and has not recovered since then, agency MBS issuance by GSEs continued to be substantial after the GFC. The main distinction between these two segments is that agency MBS carry a government credit

Table 1: Selected statistics

Mortgage market	Pre-GFC 90-06	Post-GFC 09-16	All 90-16
[1]Sales of loans (%)	61.8	77.0	66.7
[2]Corr (sales, lending)	0.96	0.98	0.97
[3]GSEs market shares			
Loan purchases	0.62	0.74	0.66
[4]RMBS issuance	0.69	0.95	0.81

Source: HMDA LARs and Reporter Panel 1990–2016. 1. The percentage of sales corresponds to the average dollar amount of loan sales divided by the total dollar amount of loans originated in a year by a reporter institution. 2. The correlation is the average correlation of the volume of loans originated and volume of loans sold (or securitized) in the cross section. 3. Data on RMBS issuance market share are from SIFMA. 4. Data on RMBS issuance market share are only available starting in 1996.

guarantee that shields investors from borrowers' credit risk.[11] A relevant institutional feature is that agency MBS are traded almost entirely in a futures market known as the to-be-announced (TBA) market. This market accounts for more than 90 percent of MBS trading volume, making it the largest liquid market for MBS in the U.S.[12]

Some characteristics of TBA trades are worth mentioning as they will guide the modeling choice of securitization in the following section. First, securities from a TBA trade are known as pass-through securities. The underlying mortgage principal and interest payments are collected by a pass-through structure and forwarded to security holders on a pro rata basis. There is no tranching or structuring of cash flows. Second, in a TBA trade, the actual identity of the securities to be delivered at settlement to a buyer is not specified on the trade date. Instead, participants agree upon general parameters for the underlying pool of mortgages. Third, the market operates under the mechanics of what is known as the cheapest-to-deliver practice; in this practice, a seller can select and deliver the lowest value mortgage pools in its inventory that satisfy the terms of trade.[13] These features of the securitization market are important to understanding the equilibrium connection and the availability of liquidity to the credit market.

[11]The credit guarantees provided by Fannie Mae (Federal National Mortgage Association) and Freddie Mac (Federal Home Loan Mortgage Corporation) are seen as either an explicit or implicit government guarantee because of their privileged status as quasi-governmental entities.

[12]According to statistics from the Securities Industry and Financial Markets Association (SIFMA). The other type of MBS trading is known as "specified pool" trading because the identity of the securities to be delivered is specified at the time of the trade.

[13]The details about TBA trading are outlined in the "good delivery guidelines" developed by SIFMA; see Vickery and Wright (2013) for an in-depth description.

2.2 Cross-sectional Distribution of Mortgage Lending

A high market concentration is the main characteristic of the mortgage industry in the United States. From 1990 to 2016, a small number of mortgage originators—although different originators over time—have dominated the lending market. Table 2 summarizes average moments that describe the cross-sectional distribution of mortgage originators based on their dollar amount of lending.[14] On average over the period of analysis, the top 1 percent of mortgage originators accounted for 62 percent and the top 10 percent for 89 percent of mortgage lending in the market.[15] I calibrate the model to internally match these cross-sectional moments. The theory developed in Section 4.3 shows how these moments are crucial in informing equilibrium prices and quantities. This information in turn defines the degree of amplification of information frictions presented in the quantitative exercise performed in Section 5.

Table 2: Moments of the distribution of mortgage lending

Moments	90-06
Market share top 1%	0.62
Market share top 10%	0.89
Market share top 25%	0.96
Lending top 10% to bottom 90%	9.22
Mean/median	18.5

Source: HMDA LARs and Reporter Panel, 1990–2006

Concentration is even higher if the definition of loan origination is based on the sources of funds, that is, the retail and wholesale channel. Stanton et al. (2014) find that the top 40 lenders accounted for 96 percent of all residential mortgage originations in 2006 when using Inside Mortgage Finance data and a definition of loan origination based on an originator's funding channel. Hence, the HMDA estimates in Table 2 represent a lower bound for the levels of concentration observed in the mortgage market.

2.3 Sources of Funding

Based on their sources of funding, mortgage originators are categorized into two main groups: retail banks (including savings banks, thrifts, and credit unions), which have access to deposits, and mortgage companies, which do not. This distinction is informative about originators' reliance on

[14]These results are very similar if one restricts the set of loans to those that are home purchase, conventional, one-to-four family property, and owner-occupied.

[15]This observation also holds when breaking down originators by type of mortgage institutions. A small fraction of banks, thrifts, and mortgage companies issue the bulk of mortgages in the market. Figure 8 in Appendix B shows that starting in the mid-1990s, the market became progressively more concentrated, peaking at the height of the 2006 housing market boom and slightly decreasing following the aftermath of the GFC. Most of the reduction in the number of originators is a result of a reduction in the number of small banks and credit unions. This finding is consistent with the findings of Corbae and D'Erasmo (2020), McCord and Prescott (2014), and Janicki and Prescott (2006), who document main trends in the commercial banking industry during the last three decades.

the securitization market as a source of capital and their likelihood of being financially constrained in their ability to fund mortgage lending.

Mortgage companies' sources of funding depend crucially on the securitization market's demand for MBS. Stanton et al. (2014) document that mortgage companies' portfolios of mortgages represent a large fraction of their assets, whereas most of their liabilities are very short term—repurchase agreements and warehouse lines of credit with maturities commonly between 30 to 45 days—which limits their ability to delay mortgage sales.[16] Consistent with the originate-to-distribute business model, from 1990 to 2016, mortgage companies sold close to 90 percent of their portfolios on average within the first year of origination (see Figure 10 in Appendix B). Moreover, mortgage companies account for an important share of mortgage lending to households. Figure 8 shows that their market share averaged 30 percent from 1990 to 2006 and has steadily increased since then, surpassing 50 percent in 2016.

Banks, on the other hand, have the option to hold mortgages for longer periods than mortgage companies according to their balance sheet capacity. If the demand in the securitization market dries up, they can still meet households' demand for credit by drawing from other sources of funding. However, many banks operating in the mortgage market also behave like financially constrained institutions. Loutskina and Strahan (2009) and Loutskina (2011) use call-report data to show that securitization enhances bank lending potential but also makes a bank vulnerable to a shutdown of the securitization market, which can induce strong credit contractions. Calem et al. (2013) document that the collapse in the private segment of the securitization market removed a major source of funding for banks. In response, financially constrained banks reduced the supply of mortgages, thereby amplifying the response of lending growth to the liquidity shock experienced during the GFC.[17]

3 The Model

3.1 Environment

Time is discrete and infinite. There are three types of agents: a borrower household, a continuum of lenders of mass one, and a government. Borrowers discount time (β^B) at a higher rate than lenders (β^L): $\beta^B < \beta^L$.

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

[16] These patterns are also documented by Jiang et al. (2020) for a larger set of non-depository financial institutions. Moreover, the authors find that these types of financial intermediaries finance themselves with twice as much equity as equivalent commercial banks.

[17] This is also consistent with patterns in the securitization market of corporate loans documented by Ivashina and Scharfstein (2010). They find that during downturns, *lead banks* are required to hold larger shares of the loans they originate, which is associated with reductions in the amount of loans that banks are willing to originate. The authors argue that this pattern is expected from financially constrained institutions.

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

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 total stock of housing H_t.

Mortgage Loans. Mortgages are modeled as long-term debt contracts with a fixed rate and perpetual geometrically declining payments. This assumption is motivated by the fact that the most prominent mortgage contract in the United States is the fixed-rate 30-year mortgage. Under this type of contract, a fraction ϕ of the remaining principal balance becomes due each period, so that the next period's principal balance and payment decay by a factor $(1-\phi)$.[18] 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 (1).

Mortgage Credit Risk and Default. I assume a family construct for the borrower household—as in Elenev et al. (2016) and Faria-e Castro (2018)—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 $\omega_t^i p_{h,t} h_t$ 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, so that default does not represent a windfall. This captures the loss of housing equity that a borrower experiences upon default by entering into foreclosure.[19] Appendix E.1 shows that the household's optimal default decision is characterized by a threshold $\bar{\omega}_t$, such that only members with $\omega_t^i \le \bar{\omega}_t$ default on their mortgages. For a given threshold $\bar{\omega}_t$, we can define the household's aggregate default rate $\lambda(\bar{\omega}_t) = Pr[\omega_t^i \le \bar{\omega}_t]$.

The maturity structure and the aggregate default rate imply the following law of motion for the stock of mortgage debt in the economy:

$$B_{t+1} = (1-\phi)(1-\lambda(\bar{\omega}_t))B_t + N_t. \tag{1}$$

[18] This representation has the advantage that the face value of all the coupon payments is $F_t = \sum_{t=0}^{\infty} \phi(1-\phi)^t = 1$. After making the first coupon payment ϕ, the amount of outstanding debt next period is $F_{t+1} = \sum_{t=1}^{\infty} \phi(1-\phi)^t = 1-\phi$.

[19] 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.

Notice that going forward, a loan originated $t \geq 1$ periods in the past has exactly the same payoff structure as another loan originated $t' > t$ periods in the past. Thus, we only need to keep track of total debt B_t.

Budget and Borrowing Constraints. The household's budget constraint is given by

$$C_t + p_{h,t} H_{t+1} = Y_t + T_t^B + (1 - \lambda(\bar{\omega}_t))\mu_\omega(\bar{\omega}_t) p_{h,t} H_t - (1 - \lambda(\bar{\omega}_t))\phi B_t + q_t N_t, \quad (2)$$

where $\mu_\omega(\bar{\omega}_t) = \mathbb{E}[\omega_{i,t} | \omega_{i,t} \geq \bar{\omega}]$ represents the expected valuation of the aggregate housing good among the household members that repaid their mortgage. The variable T_t^B represents a lump-sum tax imposed on borrowers by the government to balance its budget. Notice that default affects the household's financial conditions in three ways: first, it reduces total mortgage payments $(1-\lambda(\bar{\omega}_t))\phi B_t$; second, it reduces the remaining aggregate stock of liabilities in (1); and third, it also reduces the current aggregate stock of depreciated housing goods in (2), so borrowers internalize the effects of their default decisions.

The 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 $p_{ht} H_{t+1}$. This constraint captures regulatory loan-to-value π requirements:

$$B_{t+1} \leq \pi p_{ht} H_{t+1} \quad (3)$$

Housing Market. The housing market is segmented in the sense that only the borrower household purchases housing assets and derives utility from housing services.[20] Consequently, house prices are determined by the borrower's stochastic discount factor, as shown by equation (25) in Appendix E.1. House price dynamics affect households' balance sheets through their holdings of housing stock. It also affects households' leverage, which, in equilibrium, is key to determine households' default rates. For simplicity, I assume that the recovery value of foreclosed houses is zero, so borrowers' default represents a direct deadweight loss for lenders.[21] I also assume that the supply of housing is fixed to an amount $\bar{H}$ at every point in time.

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

$$V^B(B_t, H_t; X_t) \quad = \quad \max U(C_t, H_t) + \beta^B \mathbb{E}_{X_{t+1}|X_t} V^B(B_{t+1}, H_{t+1}; X_{t+1}), \quad (4)$$

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 (4) subject to (1)–(3).

[20]The assumption of housing market segmentation is standard in macro models with housing markets; see Greenwald (2016) and Faria-e Castro (2018). 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).

[21]This assumption can easily be relaxed to include the recovery value of the household's housing collateral in the lender's payoff function. As long as the lender faces a loss given default below the principal loaned, the mechanism is unchanged.

Lenders

Preferences and Funding. Lenders are denoted by lowercase letters with superscript j, and each lender j has preferences only over the final consumption good:

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

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 liabilities. A lender j's stock of loans is denoted by b_t^j. I assume that each lender holds a diversified loan portfolio across members of the household such that each of them is equally exposed to the aggregate default rate $\lambda(\bar{\omega}_t)$. Every period, lenders' income comes from borrowers' loan payments (i.e., a fraction ϕ of their performing portfolio matures and pays cash). This setup implies that lenders have limited sources of funding and act as financially constrained intermediaries. This implication is one of the main features of financial institutions operating in the U.S. mortgage market, as documented in section 2.

Loan Origination Technology. At the beginning of each period t, a lender draws a loan origination cost z_t^j, which is independent and identically distributed across lenders and time, and follows a continuous cumulative distribution function $F(z)$ in the bounded support $[z_a, z_b]$. The loan origination technology is linear, and each lender j originates new loans of size n_t^j at a gross cost of $n_t^j z_t^j$. This stochastic cost represents a source of idiosyncratic risk for each lender. It captures the heterogeneity in costs, lending opportunities, and expertise of a wide variety of mortgage originators.

Securitization Market. Securitization is modeled to capture key features of the TBA forward market, the largest liquid market for MBS in the U.S. (see section 2). In the model, lenders have access to a securitization market where they can buy securities and sell their stock of outstanding loans in inventory $(1-\phi)b_t^j$. A lender j makes trading decisions $\{s_{Gt}^j, s_{Bt}^j, d_t^j\}$ where s_{Gt}^j represents sales of high-quality loans, s_{Bt}^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. Hence, a 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. I 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.[22]

A TBA trade has two main features. First, a buyer learns the exact characteristics of the securities just before delivery rather than at the time of the trade. This means that sellers choose which assets in their portfolio will be delivered to buyers at settlement after information about the assets' quality has been realized. Second, TBA securities trade on a "cheapest-to-deliver basis." Under this arrangement, buyers understand that sellers have incentives to sell the lowest-value

[22]These assumptions are a tractable way of ensuring that the adverse selection problem persists over time in this simplified environment. Chari et al. (2014) show that adverse selection also persists over time when these assumptions are relaxed—that is, when lenders' reputation from trading actions is considered in an optimal contracting problem with non-exclusive markets.

assets that satisfy the terms of trade. This arrangement gives a seller an advantage to better predict the quality of a loan.[23]

Private Information. Every lender j can predict the aggregate household default rate and privately identify which loans within her portfolio are more likely to default every period (i.e., information about a loan's quality is private information). An outsider cannot make such a distinction. By the end of the period, quality becomes public since every lender can identify the non-performing loans in the economy.[24] The information asymmetries between mortgage sellers and buyers often—although not exclusively—arise during the borrower's screening stage. 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.[25] I abstract from modeling the specific sources of these information asymmetries and instead take them as part of the environment.[26] For consistency, I assume that a lender's loan origination cost remains private so that other lenders cannot use this information to infer her trading decisions. Hence, private information implies that only the total volume of a lender's loan sales is observable $s^j_{Gt} + s^j_{Bt}$, and it is not possible to distinguish sales for liquidity needs from sales for strategic motives.

In this environment, just as it is in practice, a classic adverse selection problem, as in Akerlof (1970), naturally arises. Buyers are well aware of sellers' incentives to sell low-quality loans, and they expect to receive securities valued possibly below the average stated quality. Hence, buyers of securities will face a discount—over the competitive price—that would not emerge in the absence of information frictions. Let μ_t represent the per-unit discount arising from the adverse selection problem. This is an endogenous equilibrium object, and it is defined as the aggregate fraction of low-quality loans traded in the securitization market:

$$\mu_t = \frac{S_{B_t}}{S_t}, \tag{5}$$

[23]Details about TBA trading are outlined in the "good delivery guidelines" developed by SIFMA; see Vickery and Wright (2013) for an in-depth description.

[24]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. Ex post, once the household's default rate is determined in equilibrium, it splits a lender's portfolio between performing and non-performing loans: $\{(1-\lambda(\bar{\omega}))b^j_t, \lambda(\bar{\omega})b^j_t\}$.

[25]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., loan-to-value (LTV), income, credit scores). Evidence of these information asymmetries, mainly in low-documentation loans, 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. (2015)). Asymmetries of information can arise even if both parties observe the same information. For example, originators developing superior valuation models relative to MBS buyers–models that are designed to predict a borrower's default based on fundamentals–can give rise to such asymmetries (see Shimer (2014) and Krainer and Laderman (2014)).

[26]The problem of borrowers' credit risk screening is relevant because of the scope for a moral hazard problem on the side of the originator (Downing et al. (2008) Keys et al. (2010)), Adelino et al. (2019)). For recent models addressing this problem, see Vanasco (2017), Neuhann (2019), and Caramp (2019).

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

From a modeling perspective, this securitization design combines elements from Kurlat (2013)'s model of asset creation and reallocation—to capture characteristics of the TBA market—with two key features of the credit market to model the securitization liquidity channel. 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 that the severity of information frictions, μ_t, becomes an endogenous function of market prices, the household's default rate, and lenders' trading decisions.

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

$$b^j_{t+1} \quad = \quad (1-\phi)(1-\lambda(\bar{\omega}_t))b^j_t - s^j_{Gt} + n^j_t + (1-\mu_t)d^j_t \tag{6}$$

The next period's portfolio comprises the current period's outstanding portfolio net of default, minus any loan sales, plus new loans. The last term, $(1-\mu)d^j_t$, corresponds to new purchases of securities net of the adverse selection discount imposed by information frictions. Consistent with practice, after physical settlement of a TBA trade, the buyer observes additional characteristics of the mortgage pool it has received, which provides valuable information about a security's payoff. Also, notice that the securitization technology transforms mortgage pools of heterogeneous qualities into homogeneous quality MBS. This transformation provides fungibility to an MBS and constitutes a fundamental part of its liquidity value (Vickery and Wright (2013)).

Flow of Funds Constraint. A lender's flow of funds constraint is given by

$$c^j_t + z^j_t n^j_t (q_t + \gamma_t) + p_t d^j_t (1-\tau_t) \quad \leq \quad (1-\lambda(\bar{\omega}_t))\phi b^j_t + p_t(s^j_{Gt} + s^j_{Bt}) \tag{7}$$

The right-hand side shows the sources of funding for a lender j: current mortgage payments net of losses from households' default, and cash receipts from sales of high- and low-quality loans in the securitization market. The left-hand side shows lender j's outflows: consumption c^j_t, 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. The additive term γ_t represents the guarantee fee that the government charges originators to partially finance a subsidy τ_t provided to buyers of securities. Both $\{\gamma_t, \tau_t\}$ are state-contingent government policy tools that capture current policy interventions in the market (explained below in more detail).

Notice that s^j_{Bt} shows up in the flow of funds constraint because a lender can sell low-quality loans in the current period. However, it does not show up in a lender's portfolio law of motion (6). This is because low-quality loans are assumed to have a recovery value of zero; if a lender keeps them, these become current losses as those loans do not accumulate over the next period. A lender also faces portfolio restrictions over loan sales:

$$s^j_{Gt} \in [0, (1-\lambda(\bar{\omega}_t))(1-\phi)b^j_t] \tag{8}$$

$$s^j_{Bt} \in [0, \lambda(\bar{\omega}_t)(1-\phi)b^j_t] \tag{9}$$

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

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:

$$V(b_t^j, z_t^j; X_t) = \max u(c_t^j) + \beta^L \mathbb{E}_{X_{t+1}|X_t} V(b_{t+1}^j, z_{t+1}^j; X_{t+1}) \tag{10}$$

A lender's recursive problem consists of choosing policy functions $\{c_t^j, b_{t+1}^j, d_t^j, s_{G,t}^j, s_{B,t}^j\}$ to maximize (10) subject to (6), and (7)-(9).

Government

In the agency securitization market, the GSEs insure mortgages against default risk and finance this insurance by charging a fee to the mortgage originator, known as the guarantee fee. The fee is a surcharge, in basis points, added to the loan interest rate contracted with the borrower. I model this setup as a set of exogenous state-contingent government policies. There are two policy instruments: (i) a fee on loan originators and (ii) a state-contingent subsidy to lenders that buy securities. Let γ_t represent the insurance fee in units of the discounted price for loans. Then, to lend a unit of resources, a lender must give up

$$\tilde{q}_t = q_t + \gamma_t \tag{11}$$

The subsidy on security purchases is denoted by $\tau_t > 0$. It is aimed at compensating buyers of securities for the losses derived from borrowers' default and the adverse selection problem captured by the function μ_t. Consider $\tau_t = \alpha^G \mu_t$, where $\alpha^G \in [0, 1]$ corresponds to the degree of subsidy provided by the government policy. When $\alpha^G = 1$, the policy completely offsets a buyer's losses associated with default risk; hence, $\tau_t = \mu_t$ works as a full insurance policy, which captures the post-GFC securitization market. When $\alpha^G = 0$, there is no government subsidy (i.e., $\tau_t = 0$).[27] The government budget constraint is given by

$$\gamma_t N_t + T_t^B = \tau_t p_t D_t, \tag{12}$$

where $\gamma_t N_t$ represents aggregate government revenue from collecting the origination fee. The variable T_t^B is a lump-sum tax charged to borrowers so that the government can balance its budget each period. The right-hand side represents government expenditures from providing subsidy τ_t to security buyers, and D_t is the aggregate demand of securities.

Market Clearing

From here on, the superscript j is suppressed for ease of notation, and lowercase variables represent individual lender decisions.

[27] In practice, the agency MBS segment features full insurance, whereas the non-agency MBS segment (also known as private-label securitization (PLS)) features either none or some form of partial insurance provided by a private entity. Although interesting on its own, modeling this market segmentation would require a different model. Nonetheless, the pre-GFC securitization market as a whole can be seen as a partially insured market with α_G representing the market share of GSEs in the entire MBS market.

State Variables. The set of aggregate states in the economy is given by $X_t = \{Y_t, \sigma_{\omega t}, \Gamma_t, B_t, H_t\}$. Recall that $\{Y_t, \sigma_{\omega t}\}$ are exogenous states representing the borrower household's income endowment and the volatility of the housing valuation shocks, respectively. We assume these states follow a joint Markov process with transition matrix Π. The expression $\Gamma_t(b, z)$ is the joint distribution of the stock of loans and origination costs across lenders.[28] The variables $\{B_t, H_t\}$ are the aggregate stock of loans and the aggregate stock of housing in the economy, respectively.

Market clearing in the housing market requires

$$H_{t+1} = \bar{H}. \tag{13}$$

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

$$N_t = \int n_t \, d\Gamma_t(b, z) \equiv \int b_{t+1} - b_t(1-\phi)(1-\lambda(\bar{\omega}_t)) - s_{Gt} + (1-\mu_t)d_t \, d\Gamma_t(b, z). \tag{14}$$

Whenever the equilibrium security price is strictly positive $p_t > 0$, the market clearing condition in the securitization market,

$$S_t \geq D_t, \tag{15}$$

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

The aggregate resource constraint is given by

$$C_t + \int c_t \, d\Gamma_t(b, z) + p_{ht} H_{t+1} - \mu_\omega(\bar{\omega}_t) p_{ht} H_t + \zeta(N_t) \leq Y_t, \tag{16}$$

where $\zeta(N_t) = q_t \int (z_t - 1) n_t \, d\Gamma_t(b, z)$ represents the aggregate cost of lending in the economy.

The model is fully characterized by the solution to the problem of the family of borrowers (4); the policy functions for each individual lender problem (17)-(18); the market clearing conditions for each market (14)-(15); and the aggregate resource constraint of the economy (16). Equilibrium prices $\{p, q, p_h\}$ and adverse selection discount function $\{\mu\}$ in (5) are jointly determined for every node X in the state space using global solution methods. The computational algorithm is presented in Appendix D.

3.2 Competitive Equilibrium

A recursive competitive equilibrium given government policy $\{\gamma, \tau, T^B\}$ 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 $\{c, b', d, s_G, s_B\}$ for lenders $j \in J$, aggregate law of motion for Γ' with transition density function Π_Γ, adverse selection discount function $\{\mu\}$, and price functions $\{q, p, p_h\}$ such that:[29]

[28] 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)).

[29] From here onward, time indexing is suppressed for variables in t, and variables in $t+1$ are indicated by the superscript $'$.

1. Borrowers' policy functions solve the problem in (4), taking as given $\{q, p, p_h\}$.
2. Lenders' policy functions solve the problem in (10), taking as given $\{q, p, \mu\}$.
3. The housing price p_h clears the housing market (13):
4. The price of lending $q > 0$ clears the credit market (14):
5. Whenever $p > 0$, the securitization market clears (15) and the adverse selection discount μ is determined in equilibrium by (5).
6. The aggregate law of motion Π_Γ is generated by the exogenous joint Markov process Π, the distribution of lenders idiosyncratic shocks $F(z)$, and lenders' policy functions b'.
7. The government budget constraint (12) is satisfied every period.
8. The resource constraint (16) holds every period.

4 Theoretical Analysis

This section has three parts. First, the characterization of a lender's policy functions is presented. This characterization is useful in understanding the main properties of the model, which are introduced in the second part. Parts 3 and 4 focus on the securitization liquidity channel and the transmission of household shocks between the credit and securitization markets.

4.1 Characterization of a Lender's Decisions

I characterize a lender's policy functions by solving the dynamic problem in (10) in two steps. First, a lender maximizes its wealth statically by solving a linear problem that leads to corner solutions for securitization decisions $\{n, d, s_{G,}, s_B\}$. In the second step, a lender solves a standard consumption-savings problem using the wealth function from the first step.[30] After characterizing lenders' policy functions, I derive analytical expressions for the aggregate demand and supply of securities in the securitization market, as well as for aggregate credit supply.

Linearity of Policy Functions. The lender's dynamic problem has two main properties: first, the constraint set is linear in the stock of loans b, and second, preferences are homothetic, given the assumption of log preferences. The first property implies that a lender's consolidated wealth is proportional to her stock of loans; the second implies that her consumption and investment decisions are a constant fraction of her wealth. Hence, the policy functions for all lenders' decisions $\{c, b', s_G, s_B, d\}$ are linear in their stock of loans b. This is summarized in Lemma 1.

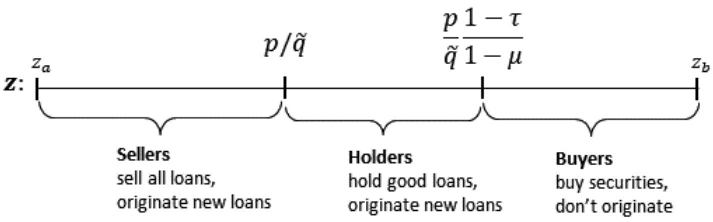
Lemma 1. Aggregate debt B is a sufficient statistic to predict prices and aggregate quantities. In particular, these do not depend on the distribution of debt holdings across lenders, only on aggregate debt B.

[30] The same characterization strategy is used in Kurlat (2013) and Bigio (2015), who develop dynamic general equilibrium models with information frictions.

Furthermore, Lemma 1 implies that it is not necessary to know the distribution Γ. The relevant set of aggregate states needed to predict prices and quantities is given by $X = \{B, H; \sigma_\omega, Y\}$.

Lending and Security Trading Policy Functions. In the securitization market, trading decisions can be characterized separately from consumption and lending decisions $\{c, b'\}$. Taking portfolio lending decisions b' as given, the problem of lender j, equation (10), consists of maximizing consumption c by choosing $\{n, s_G, s_B, d\}$, which implies solving a linear problem. Appendix E.3 shows that lenders' trading decisions are characterized according to cutoffs $\{\frac{p}{\tilde{q}}, \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}\}$ that split lenders into three groups according to their origination-cost draw $z \in [z_a, z_b]$, as shown in Figure 2.

Figure 2: Lenders' trading decisions in the securitization market



In equilibrium, lenders self-classify into three groups: sellers, holders, and buyers. Sellers are lenders with a low-z, $z \in [z_a, p/\tilde{q})$. They can originate new loans at a low cost, and because they can do this, they have incentives to sell their entire outstanding portfolio in the securitization market and use the proceeds to originate new loans. Buyers are lenders with a high-z, $z \in (\frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}, z_b]$. For them, originating new loans is very costly. The market allows them to buy securities from other lenders at a lower price relative to their origination cost. Thus, they choose to buy securities instead of originating new loans. Holders are lenders that fall between the cutoffs, $z \in [p/\tilde{q}, \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}]$. Given their origination cost, the market price is not high enough to induce them to sell high-quality loans. Moreover, because of the adverse selection discount, the effective price they must pay for buying securities is too high; therefore, they don't buy them. They end up holding their illiquid portfolio of outstanding loans and originate fewer loans at a high cost.

Lemma 2 summarizes trading and lending decisions for lenders. Trade in the securitization market is essentially an alternative lending technology to loan origination. When the securitization market is active, some lenders can specialize in lending and others in holding existing securities, meaning that they find it profitable to lend through the market instead of lending using their own technology. If the securitization market is not active, this alternative technology is not available to any lender.

Lemma 2. Given a lender's lending b', if there exists a positive market price for loans $p > 0$, the optimal trading decisions $\{n, d, s_G, s_B\}$ are shown in Table 3, where the second cutoff is well defined for $\tau \leq \mu$. If there is no positive price that clears the securitization market, trading decisions are $d = s_G = s_B = 0$, and a lender origination decision is $n = b' - (1 - \lambda(\bar{\omega}))\phi b$, taking into account the non-negativity constraints $n \geq 0$ and $d \geq 0$.

Consumption and Lending Policy Functions. Different trading decisions imply different budget sets for a lender—in particular, the budget set for lenders that become buyers or holders.

Table 3: Trading and lending decisions

	$z < p/\tilde{q}$	$z \in [p/\tilde{q}, \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}]$	$z > \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}$
d	*0*	*0*	$\frac{b'-(1-\lambda(\bar{\omega}))(1-\phi)b}{1-\mu}$
s_G	$(1-\lambda(\bar{\omega}))(1-\phi)b$	*0*	*0*
s_B	$\lambda(\bar{\omega})(1-\phi)b$	$\lambda(\bar{\omega})(1-\phi)b$	$\lambda(\bar{\omega})(1-\phi)b$
n	b'	$b'-(1-\lambda(\bar{\omega}))(1-\phi)b$	*0*

This non-convexity arises because the marginal rates of substitution are different not only across lenders but also between possible equilibrium outcomes in the securitization market.

I follow a similar strategy as in Kurlat (2013) and Bigio (2015), Appendix E.4 shows that it is possible to characterize a lender's consumption-savings policy functions by specifying a relaxed problem. The relaxed problem defines a convex budget set based on a lender's consolidated wealth before her trading decision has taken place. Then, given that lenders have log preferences, the optimal consumption-savings rule will be to lend a constant fraction β^L of her wealth and consume the rest. Lemma 3 summarizes this intuition based on the definition of a lender's relaxed problem given in (28). Furthermore, the solution to the relaxed problem coincides with the solution to the original lender's problem (10) whenever the securitization market is active (i.e., there is a positive price p that clears the market). If there is no such positive price, the relaxed problem can also be used to obtain consumption-savings policy functions in the absence of a securitization market.

Lemma 3. The optimal consumption and lending policy functions that solve problem (28) are given by

$$c = (1-\beta^L)W(b,z;X) \tag{17}$$

$$b' = \frac{\beta^L}{\tilde{q}\min\{z, \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}\}}W(b,z;X) \tag{18}$$

where $W(b,z;X)$ represents a lender's wealth function defined by (27).

4.2 Equilibrium in the Securitization and Credit Markets

Securitization Market. The supply of loans in the securitization market is obtained by integrating the policy functions of sales of high- and low-quality loans introduced in Lemma 2:

$$S = \int s_B(b,z;X)\, d\Gamma(b,z) + \int s_G(b,z;X)\, d\Gamma(b,z) \tag{19}$$

Demand for loans is obtained by integrating security purchases. For this, we use the lender's lending policy function (18) and purchasing decisions from Lemma 2:

$$D = \int d(b,z;X)\, d\Gamma(b,z) \equiv \int_{\frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}}^{z_b} \int_{b} \frac{b'-(1-\lambda(\bar{\omega}))(1-\phi)b}{1-\mu}\, dG(b)dF(z). \tag{20}$$

The adverse selection discount $\mu = \frac{S_B}{S}$ is defined in equation (5). Notice that demand is only well defined for $\mu < 1$; when $\mu = 1$, demand is zero. We repeat the market clearing condition (15):

$$S \geq D \text{ holding strict whenever } p > 0.$$

Lemma 4. $D > 0$ only if the solutions to problem (10) and problem (28) coincide for all lenders.

The solutions to problem (10) and problem (28) will differ whenever a lender chooses an allocation outside her budget set in (10). In this case, demand for securities in the securitization market will be zero, and the price must also be zero. This is formalized in Lemma 4.

Credit Market. The equilibrium in the credit market is determined by the market clearing condition (14), which equates borrowers' demand for credit with lenders' supply of credit:[31]

$$N^D = N^S$$

The aggregate supply of credit is derived by aggregating the lender's lending decisions, as presented by Lemma 2. Lending policy functions are defined for two possible scenarios: one in which loans and securities trade at a strictly positive price, and another in which the price of securities is zero. In the first case, only lenders that become sellers and holders originate new loans, and the total mass of originators is given by the integral over the interval $[z_a, \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}]$ (see Figure 2). Hence, when the securitization market is active, the total supply of credit is given by (21). In the second case, when the securitization market is not active, aggregate supply will be given by the integral of lending decisions over all lenders in the interval $[z_a, \bar{z}(q)]$, as summarized in Lemma 5.

Lemma 5. Credit supply is contingent on the equilibrium outcome achieved in the securitization market. The credit supply function is given by

$$N^S = \int_{z_a}^{\bar{z}(p,q)} n \; d\Gamma(b, z). \tag{21}$$

where the cutoff $\bar{z}(p, q)$ is given by

$$\bar{z}(p,q) = \begin{cases} \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu} & p > 0 \\ \min\left\{z_b, \frac{1}{q}\frac{\beta^L\phi}{(1-\beta^L)(1-\phi)}\right\} & p = 0 \end{cases} \tag{22}$$

4.3 Model Properties

This economy has two key frictions: first, financial markets are incomplete, in the sense that lenders have limited access to debt markets; and second, trading in the securitization market is affected by private information about the quality of loans. In the absence of both frictions, only the lowest-cost lender operates, while the rest of the lenders finance her.[32] The following analysis assumes market incompleteness and focuses on the equilibrium outcomes from relaxing information asymmetries.

Securitization with Complete Information. Lenders can identify all low-quality loans in the economy. Given that we have assumed low-quality loans pay zero units upon default with certainty, their market value is zero. In this case, there is no adverse selection in the securitization market, and only high-quality loans are traded if there is a positive equilibrium price that satisfies market

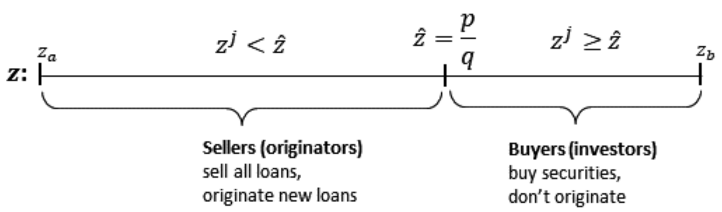
[31] The aggregate demand for credit depends on the policy function of aggregate household debt B', which is obtained by numerically solving problem (4). Once we solve the borrower's problem, we derive the aggregate demand for credit using the law of motion for the borrower's debt (1).

[32] This could be achieved by letting the lowest-cost lender issue one-period state-contingent contracts to the rest of the lenders. This equilibrium outcome provides full insurance against lenders' idiosyncratic cost(risk) and minimizes intermediation costs.

clearing. The adverse selection discount is zero, and there is no wedge between the price a lender receives and the cost a buyer pays when purchasing securities. Figure 3 shows lenders' trading decisions under complete information. If there is an equilibrium in the securitization market, it is associated with only one cutoff $\hat{z}$. All lenders with origination costs below $\hat{z}$ sell their entire portfolio in the securitization market to obtain cash and originate new loans. All lenders with origination costs above $\hat{z}$ retain their portfolio, buy securities, and do not originate new loans.[33]

The securitization market serves two primary purposes in this economy. First, it reallocates resources efficiently among lenders (allocative efficiency), and second, it eases a lender's liquidity needs. A lender obtains liquidity by selling—either partially or completely—her portfolio of outstanding loans instead of collecting payments until loans mature. Without a securitization market, the liquidity available to a lender is limited to the cash payments from the lender's maturing portfolio.

Figure 3: lenders' trading decisions under complete information



The reallocation of resources among lenders occurs because lenders value their outstanding loan portfolios differently. They do this because of differences in loan origination costs. This heterogeneity gives rise to gains from trading assets. The most efficient lenders—those who draw a low z—have a low valuation for their outstanding portfolios and want to sell them because they can invest at a higher return by originating new loans. The least efficient lenders—those who draw a high z—have a high valuation for their outstanding portfolios. They value their portfolios differently because originating new loans is more expensive than holding illiquid assets; hence, purchasing securities becomes a more profitable strategy. In this sense, the securitization market increases the efficiency of credit funding by providing liquidity to the most efficient lenders and reallocating illiquid assets toward those whose cost of holding them is lower .

Credit intermediation is a costly process. By accessing a securitization market, lenders can trade away their differences in intermediation costs and reduce their individual cost of lending, and, hence, the average cost of lending for the economy.[34] Securitization leads to an efficient reallocation of liquid funds toward the lowest-cost lenders. This is the securitization liquidity channel: in the aggregate, credit supply expands, and borrowers enjoy lower interest rates. This intuition is formalized in Proposition 1.[35]

[33] This specialization by activity resembles the specialization observed in the mortgage market. That is, some financial institutions specialize in issuing loans, while others specialize in holding and investing in securities.

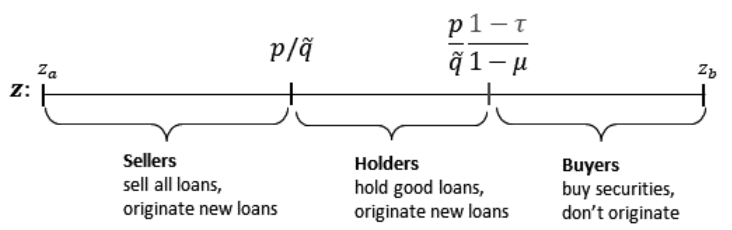
[34] Additionally, since lenders consume and invest in fixed proportions, a fraction of those extra resources—gained through an efficient reallocation—also increases their lending.

[35] Vickery and Wright (2013) and Fuster and Vickery (2014) document this mechanism, finding that TBA eligibility is associated with an inflow of liquid funds and lower (fixed) mortgage interest rates in the residential market.

Proposition 1. *Under complete information, in the steady state, an economy with trade in the securitization market features lower mortgage rates relative to the absence of trade in this market (i.e., the discounted price of mortgage debt satisfies:* $q^{CI} > q^{NSM}$*).*

Securitization with Private Information. The impossibility of publicly identifying low-quality loans in the securitization market creates an adverse selection problem. Sellers are better informed about the default risk of the loans they sell, and they actively benefit from this information advantage. As shown in Lemma 2, lenders choose to always sell their low-quality loans and retain the high-quality ones strategically. Hence, sellers adversely affect buyers in the securitization market. Although a buyer pays p for one security, she only obtains $1 - \mu$ units because of the adverse selection discount. Information frictions generate a wedge between the relative price of securitizing loans and the effective cost of buying securities, as depicted in Figure 4. This endogenous wedge captures the severity of information frictions in the market. By disrupting securitization, information frictions reduce the asset reallocation process and the flow of liquid funds for new credit, and increase intermediation costs.

Figure 4: lenders' trading decisions under private information



An important property of the model is that adverse selection can rapidly become severe when the household default rate increases. This is a source of volatility and amplification of credit cycles. It occurs because many lenders switch from selling or buying to retaining their high-quality loans when they expect the average quality of securities to fall.[36] This mechanism is at the heart of the adverse selection multiplier of household shocks. And also captures 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.

Proposition 2 establishes that episodes of market shutdown are possible in this economy. This characteristic is also present in models of static (Akerlof (1970) and Stiglitz and Weiss (1981)) and dynamic adverse selection (Guerrieri and Shimer (2014), Kurlat (2013), and Chari et al. (2014), among others). My framework goes one step further by providing an equilibrium connection between securitization and the credit markets instead of modeling them as a single market. So even

[36]Elul (2011) presents empirical support for this mechanism in the years leading to the GFC. He finds that in 2005, the average quality of retained loans was not significantly different from that of loans sold, whereas starting in 2006, the average quality of loans sold worsened compared with those retained. Agarwal et al. (2012) also document that starting in 2007, the strategy of prime mortgage originators moved toward an unwillingness to retain higher-default-risk loans in return for a lower prepayment risk, which coincides with the beginning of the foreclosure crisis in the credit mortgage market.

when the securitization market ceases to operate, the credit market continues functioning, and the economy can transition between states in which the securitization market is active and inactive.

Proposition 2. *In an economy with private information, in the steady state, a sufficient condition for a securitization market shutdown is*

$$\min_p \left\{ \frac{p(1-\tau)}{1-\mu} \right\} > \frac{\beta\phi}{(1-\beta)(1-\phi)}, \quad \textit{then:} \tag{23}$$

1. *the securitization market does not operate.*

2. *in the credit market, each lender originates loans with her own technology.*

3. *the mortgage rate is higher than when the securitization market operates.*

Condition (23) has the intuitive interpretation that the market effective cost of buying securities cannot be larger than the lending cost for the highest-cost lender in the economy defined by (22). This condition also shows that the subsidy policy plays a role in reducing the probability of market collapse. The subsidy policy satisfies $\tau_t \leq \mu_t$. Thus, any positive level of subsidy reduces the asymmetric information wedge by moving the second equilibrium cutoffs further left from the upper bound z_b, which increases the mass of security buyers. However, a sufficiently large deterioration in loan quality derived from higher household default rates can lead to market collapses in the case of a partial subsidy, as lenders still bear a fraction of borrowers' credit risk. Section 5 shows that this is the case for the pre-GFC economy where the subsidy is calibrated to match the fraction of agency-guarantee MBS out of the total market.

Subsidy Policy. The most well-known policy in the U.S. agency securitization market is the credit risk guarantee provided by GSEs to mortgage security investors. In this environment, such policy is captured as a state-contingent subsidy $\tau_t = \alpha_G \, \mu_t$, where $\alpha_G \in [0, 1]$ represents the degree of insurance provided by the policy. The endogenous wedge arising from information frictions—expressed as the distance between the two cutoffs in Figure 4—is given by $\frac{p_t}{\tilde{q}_t}\frac{1-\tau_t}{1-\mu_t} - \frac{p_t}{\tilde{q}_t} \equiv \frac{p_t}{\tilde{q}_t}\frac{\mu_t}{1-\mu_t}(1-\alpha_G)$. This wedge is a decreasing function of the subsidy's coverage. Setting α_G equal to one works as a full insurance policy by completely offsetting a buyer's losses associated with default risk.

A full subsidy policy counters adverse selection by modifying a buyer's effective cost to purchase. As security demand remains stable regardless of household risk, more sellers have incentives to sell high-quality loans, which improves the average quality in the market. Aggregate liquidity is high and stable, and the probability of a market collapse is minimized.[37]

Proposition 3. *In an economy with private information, in the steady state, a full subsidy policy,* $\tau_t = \mu_t$*, generates inefficiently high liquidity compared to the complete information economy.*

[37]The full subsidy policy may not completely shield the market from a shutdown since the policy depends on the insurer's capacity to finance the associated expenses in all possible states of the economy. Consider the case in which the insurer has limited resources $\mathcal{M} > 0$. Aggregate losses must satisfy $p_t\tau_t D_t \leq \mathcal{M}$. A sufficiently high spike in household defaults could still lead to insurer insolvency. From (5), we can see that $\tau_t = \mu_t > \lambda_t$ as security buyers always keep their high-quality loans. This implies that $p_t\tau_t D_t \geq \lambda_t p_t D_t$, suggesting that an alternative policy in which the government purchases all mortgages in the economy and securitizes them can deliver financial stability at a lower cost—provided that $\lambda_t p_t D_t < \mathcal{M}$.

Although this policy achieves full asset reallocation, it does not achieve the complete information allocations. Two lessons emerge. First, the policy generates inefficiently high levels of liquidity (Proposition 3). The policy works by increasing the volume of high-quality loans securitized without changing the volume of securitized low-quality loans. In the aggregate, the volume of MBS issuance is higher and of lower average quality compared to the complete information economy in which all low-quality loans are screened out. This result hinges on the trade-off between quality and liquidity experienced by the TBA market's participants. It also explains why originators with higher-value loans might prefer to participate in the less liquid specified-pool market, which commands higher prices.[38] Along this line, the TBA securitization model can be interpreted as a framework with low screening and inefficiently high liquidity (Vanasco (2017)). A relevant insight is that a full insurance policy might affect originators' incentives to determine a loan's quality (moral hazard).

Second, although the policy minimizes intermediation costs, borrowers might not enjoy mortgage rates that are as low as the complete information economy. The guarantee fee charged to lenders distorts their optimal lending decisions and increases the price of credit in equilibrium. Section 5 studies the quantitative properties of the model in the infinite horizon setup and confirms these insights. A full subsidy policy provides financial stability in the form of lower volatility of prices and quantities, and a lower probability of market collapse. However, it fails to realize high welfare gains for households because lenders increase the mortgage rate to compensate for the guarantee fee. Also, households pay higher taxes since financing this policy requires higher tax pressure on borrowers and lenders.

Comparative Statics. Here, I establish how aggregate shocks to households transmit and feed back to aggregate outcomes in the securitization and credit markets.

Lemma 6. In steady state, consider an exogenous increase in the volatility of G_ω so that the new distribution G'_ω is a mean-preserving spread. Ceteris paribus, borrowers' default rate, $\lambda(\bar{\omega})$, under G'_ω will be higher than under G_ω.

Lemma 6 establishes that exogenous changes in the aggregate volatility of the individual housing valuation shocks induce fluctuations in households' default rates. A similar outcome can occur when income shocks stress households' balance sheets.

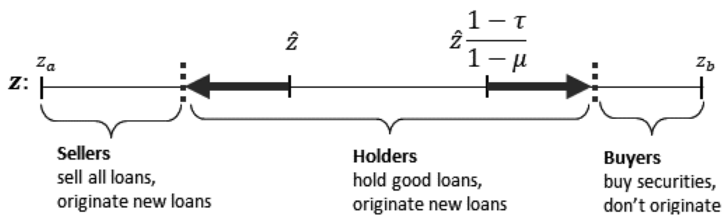
Lemma 7. In steady state, the adverse selection discount $\mu(\lambda(\bar{\omega}), \hat{z})$ is an increasing function of borrowers' default rate $\lambda(\bar{\omega})$ and decreasing in the market cutoff $\hat{z} \equiv \frac{p}{\tilde{q}}$.

Lemma 7 indicates that in times of high default risk, the proportion of low-quality loans in the market is also high. Recall that, as established in Lemma 2, lenders always sell their low-quality loans. In the securitization market, a higher discount per security will, in turn, increase the real cost of buying securities, which then contracts demand; that is, the second cutoff moves to the right in Figure 5. This is a corollary of Lemma 7. Then, the price must fall in order for the securitization market to clear. Consequently, the volume of trade is lower because at a lower price, more lenders retain their high-quality loans instead of selling them (i.e., more lenders become

[38]The specified pool market offers menus of prices for pools of loans with specific characteristics (defined by the use of "stips").

holders). Notice how a lender's illiquidity is a force that depresses the price of securities. These insights are formalized in Proposition 4.

Figure 5: Effects of episodes of high default



Proposition 4. *In steady state, consider an exogenous increase in the volatility of G_ω so that the new distribution G'_ω is a mean-preserving spread. Then, if there is a price that clears the securitization market in the new steady state, it has the following characteristics:*

1. *A higher proportion of low-quality loans are traded.*

2. *The volume of trade is lower.*

Furthermore, the aggregate cost of lending increases when the default rate is high because a larger mass of holders originate new loans at a higher cost. In the credit market, borrowers' needs for credit also increases because of housing foreclosures.

Up to this point, the theory shows that household shocks can be transmitted between both markets through the securitization liquidity channel. Section 5.3 shows that data (cross-sectional moments of mortgage lending) are informative about the magnitude of the amplification of information asymmetries.

5 Quantitative Analysis

5.1 Calibration and Estimation

The model is calibrated at an annual frequency for the period 1990–2006.

Preferences. The calibration for borrowers is standard. The discount rate β^B is set to 0.97 to match the ratio of consumption of non-durables and services to disposable personal income from the national income and product accounts (NIPA), which equals 0.79. The housing preference parameter θ is set to 0.13 to match the ratio of non-durable consumption to housing, C/H, to the ratio of consumption of non-durables and services to residential real estate: 0.4 in NIPA. The parameter governing the borrowing constraint π is set to 0.425 to match the ratio of households' mortgage debt to the stock of residential real estate in the flow of funds accounts. For lenders, the discount rate β^L is set to 0.985 to match the average real risk-free rate obtained from a one-year Treasury bill, which is 1.6% for 1990–2006.[39]

[39]In the model, lenders do not have access to a risk-free bond; however, it is possible to compute the risk-free rate corresponding to a one-period risk-free bond by computing the stochastic discount factor based on the aggregate consumption that the family of lenders obtains: $\frac{1}{1+r^f} = \beta^L \mathbb{E}_{X'|X}[U_{c'}/U_c]$, where $U_c = \frac{1}{\int c^j \, d\Gamma(b,z)}$.

Technology. The distribution of origination cost across lenders, $F(z)$, is modeled as a beta distribution characterized by shape parameters (α, β) with support $[z_a, z_b]$. These parameters are estimated by simulated method of moments (SMM) to match the market share of the top 25 percent of originators and the ratio of the average volume of mortgage origination of the top 10 percent to the bottom 90 percent of originators. These are key moments from the cross-sectional lending distribution in the HMDA panel of mortgage originators that spans the period 1990 to 2017.[40] The support of the distribution is obtained by setting the location parameter $lc = z_a$ to match the average real mortgage rate of 5.3 percent for the period 1990–2006 and by normalizing the scale $sc = z_b - z_a$ to 1. The parameter ϕ is set to 0.21 and governs the duration of the bond. I follow Elenev et al. (2016), who estimate this parameter by matching the Macaulay's duration and the coupon payments structure of a representative mortgage bond given by Barclays MBS index.

Government Policy. The government's vector of policy instruments is given by $\{\gamma, \tau, T^B\}$. In practice, GSEs charge a guarantee fee to mortgage originators—quoted in basis points over the interest rate contracted with the borrowers—and provide a level of insurance to buyers of securities. This policy can be mapped to the model using the following equation:

$$r^*(q_t) = r(\tilde{q}_t) + g_f,$$

where $r^*(q_t)$ is the interest rate implied by the discounted price q_t that borrowers face, $r(\tilde{q}_t)$ is the net interest rate obtained by the lender, and g_f is the guarantee fee. Using the definition of lenders' discounted price with government policy (11), we obtain the following relation:

$$\gamma = \tilde{q} - \left(\frac{g_f}{\hat{\phi}} + \frac{1}{\tilde{q}} \right)^{-1},$$

where γ is the fee paid by originators in the model. The guarantee fee is set to 20 basis points in the benchmark economy, the average for the period 1990–2006, as reported by Fannie Mae. The parameter governing the degree of subsidy in the securitization market, α^G, is set to the average market share of GSEs of all sales of mortgages in the securitization market, which was 69 percent for the period 1990–2006.

Aggregate Exogenous Processes. Borrower households' income Y and the variance of the housing valuation shocks σ_ω are the two exogenous aggregate states in the economy. I assume they follow a first-order joint Markov process, characterized by state space $(Y_t, \sigma_{\omega t}) \in \mathcal{Y} \times \mathcal{S}$ and transition matrix Π. For income, I use the cyclical component of disposable personal income from the flow of funds account. The mean of housing valuation shocks is set to match the average depreciation rate in the housing market, and the variance is calibrated to replicate the national delinquency rate for mortgage loans that are 90 or more days delinquent or went into foreclosure according to the National Mortgage Database from the Federal Housing Finance Agency (FHFA). I set $(\sigma_\omega^H, \sigma_\omega^L) = (5.7\%, 17.5\%)$, which obtains default rates $(\lambda^H, \lambda^L) = (1.8\%, 7.9\%)$ and an unconditional default rate of 2.6%.

[40] The choice of moments is motivated by the analysis in Section 2.2 (see Table 2). 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.

5.2 Model's Fit

This section shows the model's performance in terms of targeted moments and non-targeted moments, and shows the results from a simulation with the same sequence of shocks, as observed during the GFC. Table 4 shows the benchmark calibration and the targeted moments.

Table 4: Model versus Data Moments

Parameter		Target, period 1990-2006	Data	Model
Preferences				
β^L	0.985	risk-free rate (pp)	1.6	1.7
β^B	0.97	C/Y, consumption to disposable personal income	0.79	0.80
θ^B	0.13	C/K, consumption to real state stock	0.40	0.40
π	0.43	B/K, household mortgage debt to real estate ratio	0.43	0.43
ν	2.0	I/K, residential real estate investment ratio	0.04	0.04
μ_ω	0.975	B/K, residential housing depreciation	0.03	0.03
ϕ	0.21	Average maturity of mortgage bond index	3.7	3.7
Lenders technology, $F(z)$				
α	4.20	Market share top 25% originators	95.7	95.9
β	2.25	Average lending top-10 to top-90	9.3	9.2
lc	0.63	30 years FRM real (pp), Freddie Mac	5.0	5.1
Government policy				
α^G	0.69	GSEs market share of mortgage sales in SM, 90-03 & 90-16		
g_f	20	Avg insurance fee (bps), Freddie Mac & Fannie Mae, 90-06		

The model fits the data well. In the credit market, the model does a good job in matching the market share of the top 25 percent originators in the cross-sectional distribution. In terms of non-targeted moments, Table 5 shows that in the securitization market, the model has a good fit with the correlation between the volume of sales and the volume of loan originations to households. The model predicts a slightly higher fraction of securitized loans relative to the data. It also has a very good fit with the distribution of market shares in quartile groups across mortgage originators (Table 6).

Table 5: Non-targeted moments. Model's benchmark calibration

Description	Model	Data	Description. Period 90-06
Fraction of loan sales(pp)	73.9	61.8	% average sales of loans, HMDA
Corr (sales, lending)	0.86	0.90	Time series, HMDA
mortgage spread (bps)	178	330	Avg 30y FRM compared to 10y T-bill.

Table 6: Cross-sectional distribution of lending

Market share by quartile group	Q1	Q2	Q3	Q4
Data	0.002	0.008	0.030	0.959
Model	0.006	0.007	0.030	0.957

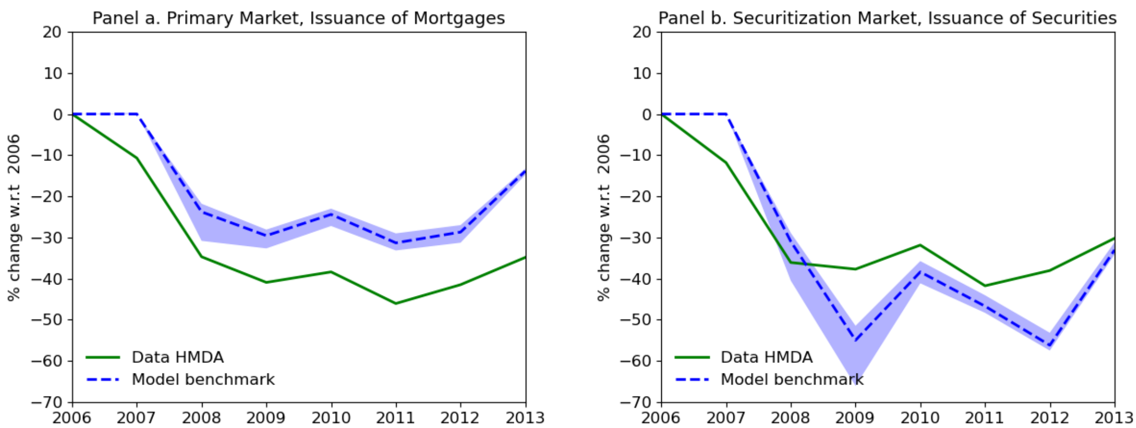
5.3 Dynamic Responses

This section studies the model's predictions on aggregates in the mortgage market during the GFC. The baseline calibration corresponds to the period 1990–2006. Introduced in the model as exogenous processes are a sequence of realized shocks for aggregate household income and a sequence of housing valuation shocks that endogenously match the default rates observed from 2006 to 2016. Figure 11 in Appendix B shows the entire sequence since 2000.

The model accounts for two-thirds of the 41 percent contraction in aggregate residential mortgage lending observed from 2008 to 2013. Figure 6 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 volume of MBS issuance fell by 37 percent on average between 2008 and 2013, and the model predicts an average decline of 40 percent during the same period. Figure 14 in Appendix C shows the percentage changes with respect to 2006 for household default rates and for the spread on mortgage interest rates. Both closely follow the observed patterns of their data counterparts during the period of analysis.

The model's success in generating large fluctuations rests on two factors. The first factor is the endogenous adverse selection multiplier that amplifies the effects of household shocks. The second is the characteristics of the cross-sectional distribution of mortgage lending. To illustrate the importance of the latter, Figure 13 in Appendix C shows the model's implied distribution of lending costs.[41] The calibrated density shows that there is a small mass of low-cost lenders—those

Figure 6: The mortgage market during the Great Financial Crisis



Panel a: Data is the aggregate volume of new mortgage issuance in a given year in dollar amounts. Source: HMDA database. Panel b. Data, Sales corresponds to the aggregate volume of sales of mortgage loans in the securitization market in a given year in dollar amounts. Source: HMDA database. All data series have been deflated to 2015 prices.

[41]The cutoffs are obtained for the mean default rate and the mean income shock.

below the first cutoff $\hat{z}$—and a large mass of high-cost lenders. The theory predicts that low-cost lenders will specialize in originating loans, while high-cost lenders will prefer to hold securities. Hence, this structural feature of the U.S. mortgage market—a small mass of lenders accounting for a large fraction of lending in the market—informs the model about equilibrium prices and indicates that the liquidity benefits of trading in the securitization market are large. The left panel in Figure 13 shows a large discontinuity in the volume of lending. The last marginal securitization seller originates a volume that is four times larger than the next marginal holder. This high dependence on securitization liquidity 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).

Based on this market structure, the model predicts that fluctuations in the aggregate default rate induce changes in the distribution of sellers, holders, and buyers, which in turn can induce large fluctuations in the supply of credit in the credit market. In particular, times during which the default rate is high can result in large contractions in the volume of new mortgage lending because some of the most efficient lenders—with large market share—switch from selling their portfolios to holding them. Thus, the cross-sectional data play a key role in informing the model's quantitative magnitude of induced fluctuations.

5.4 Quantifying Information Frictions

How important are information frictions in accounting for fluctuations in aggregate credit? To answer this question, I decompose the forces underlying the contraction. First, I simulate an economy with complete information for the same sequence of household income and housing shocks used in the pre-GFC economy. In a complete information economy, low-quality loans are identified by all lenders in the economy and, hence, not traded in the securitization market. Still, security buyers are affected by fluctuations in household default risk, which has an impact on a security's payoff.

Figure 7: Shock Decomposition during the Great Financial Crisis

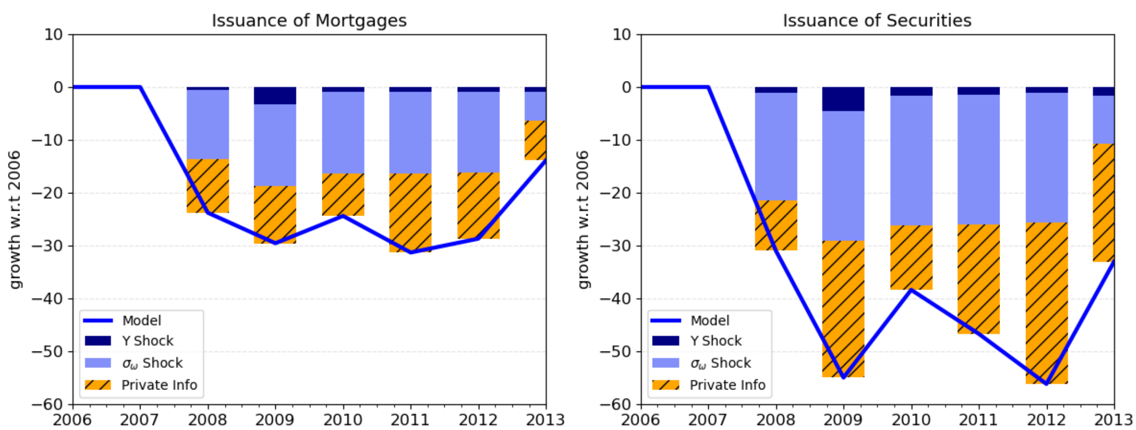


Figure 7 shows the shock decomposition for both aggregates in the credit and securitization markets. The yellow dashed bars quantifying the contribution of private information correspond to the difference between the benchmark economy and an economy with complete information. The contribution of the exogenous shocks is obtained by turning off one shock at a time in an economy with complete information.

Table 7: Average contribution of forces during 2008–2013

Contribution (pp)	priv. info	σ_ω^2	Y
Credit Market	43	52	5
Securitization Market	46	50	4

Table 7 shows that, on average, 40 percent of the model's predicted decline in mortgage lending arises from information frictions. Put differently, there is a 1.5 multiplier effect of adverse selection through the securitization liquidity channel, indicating that information frictions could have amplified the aggregate credit contraction. Extrapolating the model to the data, mortgage credit would have contracted on average by 27 percent instead of the 41 percent observed during the GFC. 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. This result is consistent with 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)).

5.5 Evaluating the Post-GFC securitization market

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 in place only the agency MBS segment from 2008 onward. A fully guaranteed securitization market is captured by increasing α^G from 69 to 100 percent. The second change was the increment of the guarantee fee γ charged by GSEs to mortgage originators. After 2012, this fee went up from 20 to 60 basis points on average. Table 8 reports unconditional means and standard deviations for selected statistics in the credit and securitization markets, and for government variables obtained from simulating alternative economies for 10,000 periods with one change at a time.

The post-GFC economy features lower volatility of quantities and prices in both credit and securitization markets when compared to the pre-GFC benchmark economy. In the credit market, the volatility of the interest rate falls from 6.3 to 4.7 percentage points, reflecting higher stability in mortgage rates. This magnitude of change is consistent with the observed decline in the volatility of the mortgage spread in the data, which fell by about 60 percent between the periods 1990–2006 and 2013–2018, as shown in Table 14 in Appendix B.

In the securitization market, the volatility of the price of securities also falls substantially, declining from 11.3 in the pre-GFC economy to 9.2 percent in the post-GFC economy. The decomposition columns in Table 8 show that the reduction in the volatility of the mortgage rate spread and in

Table 8: Policy changes after the Great Financial Crisis

Description	Pre-GFC	$\Delta^{+}\tau$	$\Delta^{+}\gamma$	Post-GFC
Credit Market				
Mortgage spread	3.29	2.61	3.56	2.90
Mortgage spread, std	6.3	4.8	6.1	4.7
Default rate	2.7	3.2	2.6	3.0
Securitization Market				
Fraction of loans traded	85.1	100	85.7	100
Price of securities, std	11.3	9.2	11.3	9.2
Prob. of market collapse	6.3	0.0	6.1	0.0
Government Policy				
Costs of policy, $\tau = \alpha^{G}\mu$	6.8	11.8	6.5	11.2
Borrower's share of tax	29	39	0	15

*All numbers are in percentage points. Moments obtained from simulating the model for 10,000 periods.

the price of securities comes from increasing the subsidy. By guaranteeing full insurance to the entire market, there is always trading in the securitization market. This finding implies that all lenders classify as either sellers or buyers, and no lenders are left holding on to their portfolio of high-quality loans. The adverse selection multiplier dampens, and security prices become insensitive to default rate fluctuations but still fluctuate as a result of the general equilibrium effect from borrowers' demand for new lending.

Overall, the model predicts that the mortgage spread settles below the level of the benchmark economy. The increase in the subsidy implies a reduction of 70 basis points in interest rates, which comes from a more efficient reallocation of assets through the securitization market. Increasing the fee on originators pushes the mortgage spread up, and mortgage originators pass on part of the tax in the form of higher interest rates to households in the credit market. A more stable mortgage market comes at the cost of higher taxes for both borrowers and lenders. The cost of expanding the government subsidy in the securitization market increases substantially from 6.8 to 11.8 percentage points in consumption units. Raising the guarantee fee on originators reduces the tax burden on borrowers. Furthermore, it implies a lump-sum transfer to borrowers from lenders.

Table 9: Welfare effects: policy changes after Great Financial Crisis

Description	Post-GFC	Decomposition	
		$\Delta^{+}\tau$	$\Delta^{+}\gamma$
Δ% Borrower welfare	0.06	-0.16	0.18
Δ% Non-durable cons.	-0.15	-0.69	0.47
Δ% Housing good cons.	0.55	2.63	-1.89
Δ% Lenders' welfare	1.3	3.01	-1.53

*Moments obtained from simulating the model for 10,000 periods. Changes in welfare are in consumption-equivalent units with respect to a pre-GFC benchmark economy.

A welfare analysis of the post-GFC economy shows positive but unequal welfare gains among borrowers and lenders. Table 9 shows that the policy changes introduced after the GFC imply small welfare gains for borrowers and larger welfare gains for lenders. The decomposition shows that borrowers benefit from lower interest rates and lower volatility. However, the increase in taxes subdues these welfare gains. For lenders, the gains from stabilization in the securitization market are higher because the subsidy policy has the additional benefit of improving lending efficiency, which reduces their lending costs and allows them to consume more. I see this welfare outcome as an upper bound on the potential benefits of the policy. Since a full subsidy policy could also influence a mortgage originator's incentives to affect the quality of loans (moral hazard). Although not the focus of this paper, a relevant aspect of a full subsidy policy is that it could also influence a mortgage originator's incentives to affect the quality of loans (moral hazard). Hence, I see this welfare outcome as an upper bound on the potential benefits of the policy.

6 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 in which information frictions play a central role. I develop a theory consistent with the U.S. mortgage market structure that is 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); Vickery and Wright (2013); Fuster and Vickery (2014)). An endogenous securitization market alleviates originators' liquidity needs and increases lending capacity. The model provides a microfoundation for how securitization can lower intermediation costs and lead to lower mortgage interest rates. However, as in practice, its benefits are 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 quality of securitized loans.

I use this framework to quantify the amplification effect of information frictions in aggregate mortgage credit and MBS issuance volumes during the GFC. I find that information frictions in the securitization market could have amplified 1.5 times the observed mortgage credit contraction. Pointing to a large adverse selection 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. To the best of my knowledge, my paper is the first to quantify the aggregate effects of information asymmetries in the mortgage market through a securitization liquidity channel.

On policy grounds, the model 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, my model shows that the credit guarantee policy of GSEs provides financial stability by reducing the volatility of prices and quantities and the probability of a market collapse. However, the policy generates inefficiently high levels of liquidity and fails to realize high welfare gains for households. Quantitatively, I find that lenders pass through the guarantee fee to households by charging higher interest rates. Also, households pay higher taxes since financing this policy requires higher tax pressure. Similar to Elenev et al. (2016), although our models differ with respect to their underlying frictions, I also find that credit guarantees were underpriced before the GFC and are still marginally so in the post-GFC economy. Hence, my results complement existing studies of the credit guarantee policy of GSEs from a general equilibrium perspective.

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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 2. 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 1990-2016. 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 2016 the HMDA panel covers 8,127 mortgage reporters every year on average.

Table 10: 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
2014-2017	.csv	Source: Consumer of Finance Protection Bureau. `https://www.consumerfinance.gov/data-research/hmda/`

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. I compute the cyclical component, Hodrick-Prescott filter, of Households Disposable Personal Income from the Flow of Funds account divided by GDP deflator (2015 base). Source: Table F.101 Households and Nonprofit Organizations.

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 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

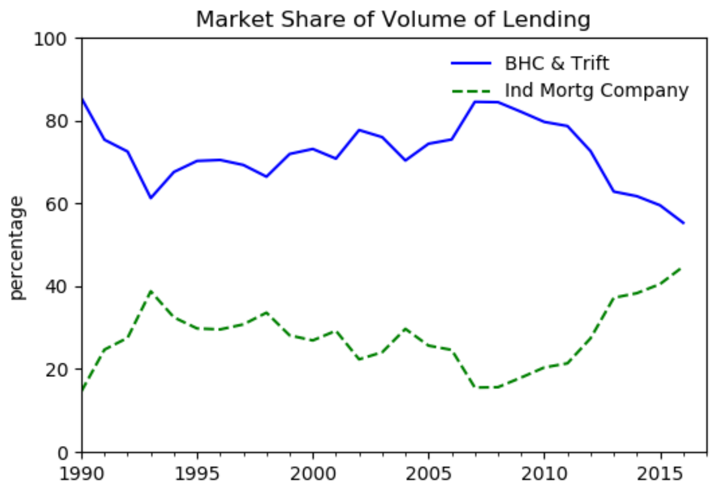
B.1 Cross-sectional characteristics of the mortgage market

Table 11: Moments of the distribution of mortgage lending

Moments	**90-06**	**90-16**
Market share top 1%	0.62	0.64
Market share top 10%	0.89	0.90
Market share top 25%	0.96	0.96
Lending top 10% to bottom 90%	9.22	9.30
Mean/median	18.5	18.9
Average number of institutions	8,596	8,206

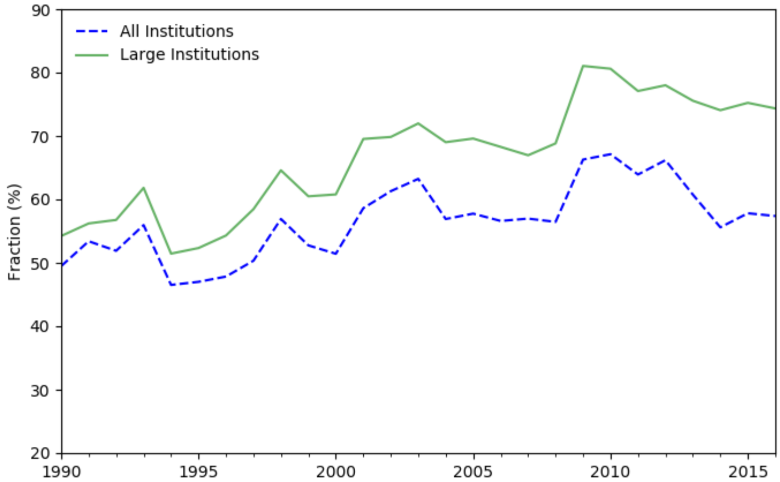
Source: HMDA LARs and Reporter Panel 1990-2017

Figure 8: Primary mortgage market, market share of the volume of lending



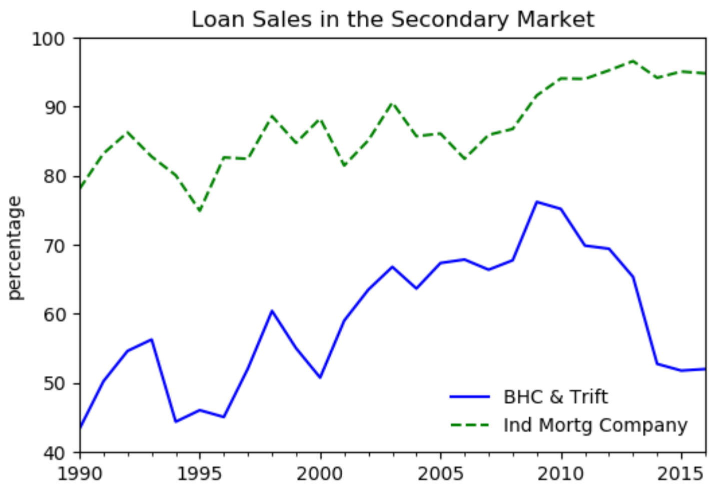
Source: HMDA LARs and Reporter Panel 1990-2017.
BHC & Thrifts refers to Bank Holding Companies and Thrifts Holding Companies including their affiliates. This category also includes savings institutions like Credit Unions.

Figure 9: Fraction of mortgage sales



Source: HMDA. The fraction of sales corresponds to the cross-sectional average aggregate dollar amount of mortgage sales divided by the aggregate dollar amount of lending for a mortgage reporter institution, for loans originated within the year that are reported. Large reporters are institutions reporting more than 1,000 new mortgage loans every year.

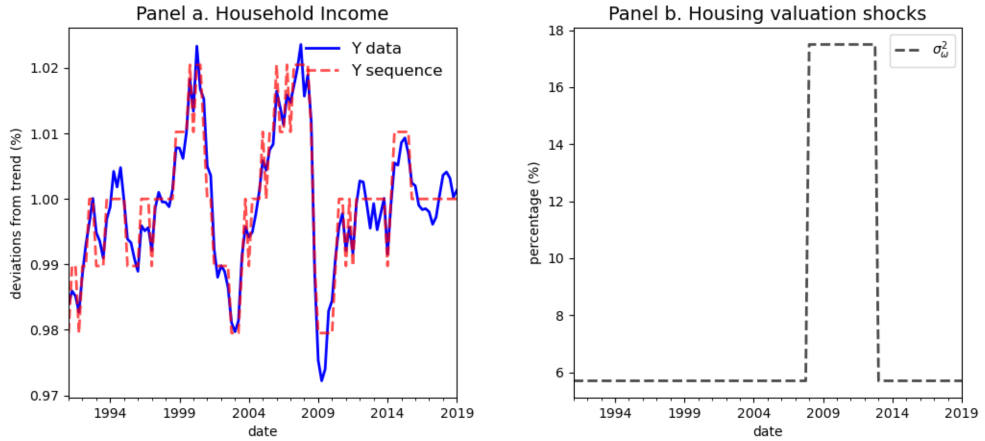
Figure 10: Sales by type of Institution



Source: HMDA LARs and Reporter Panel 1990-2017.
BHC & Thrifts refers to Bank Holding Companies and Thrifts Holding Companies including their affiliates. This category also includes savings institutions like Credit Unions.

B.2 Households Income and Default Rates

Figure 11: Income and default processes



Panel a. Household Income corresponds to the cyclical component of Disposable Personal Income from NIPA.
Panel b. Sequence of housing valuation shocks needed to match the moments of the default rate (percentage of delinquent mortgage loans 90 days or more, or in foreclousure). Source: National Mortgage Database, FHFA.

B.3 Estimation of Exogenous Processes

Households' income state space and transition matrix is obtained from the cyclical component of the Disposable Personal Income from the Flow of Funds account. First, I estimate an auto-regressive model of first order, AR(1), for the period of analysis 1990-2006, and discretize the AR processes into a Markov chain of first order. Then, I combine this process with a first order Markov chain for the housing volatility shock with two states.

Table 12: Joint Markov Process for income and default rates

State	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8	s_9	s_{10}
Y	0.980	0.980	0.990	0.990	1.000	1.000	1.010	1.010	1.020	1.020
σ^2_ω	0.078	0.203	0.078	0.203	0.078	0.203	0.078	0.203	0.078	0.203
Stationary Prob										
Prob	0.035	0.028	0.176	0.074	0.340	0.035	0.244	0.006	0.062	0.000

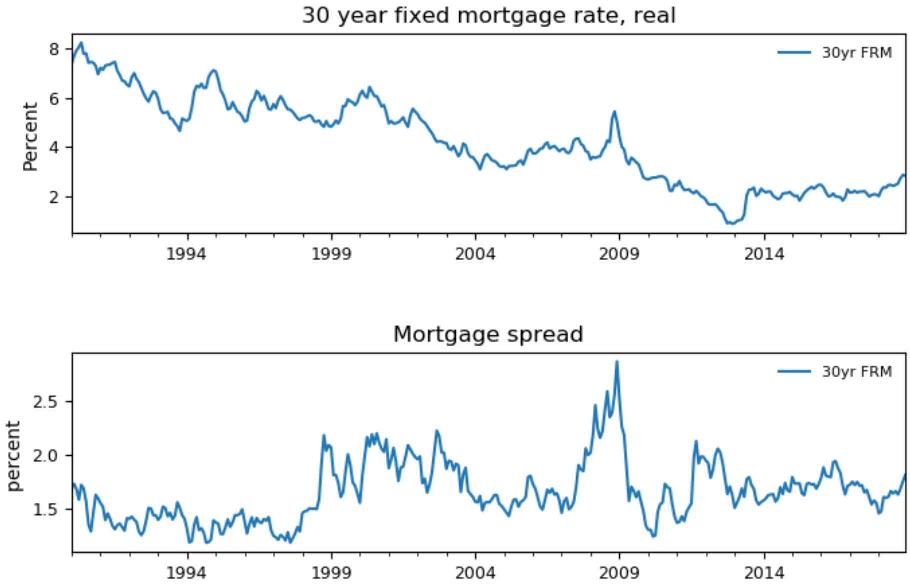
The Markov process fits well the unconditional means and standard deviations for income, and default rate, and the negative correlation between income and delinquency rates. Table 13 shows the moments obtained from a simulated time series of 100,00 periods versus the data moments

Table 13: Fitted moments for time series

	mc simulation	data, 90-06
Y mean	1.0	1.0
Y std	0.010	0.010
ρ_Y std	0.69	0.69
corr(Y,σ^2_ω)	-0.35	

B.3.1 Mortgage Interest Rates

Figure 12: Historic mortgage interest rates



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

Table 14: Historic average mortgage rates

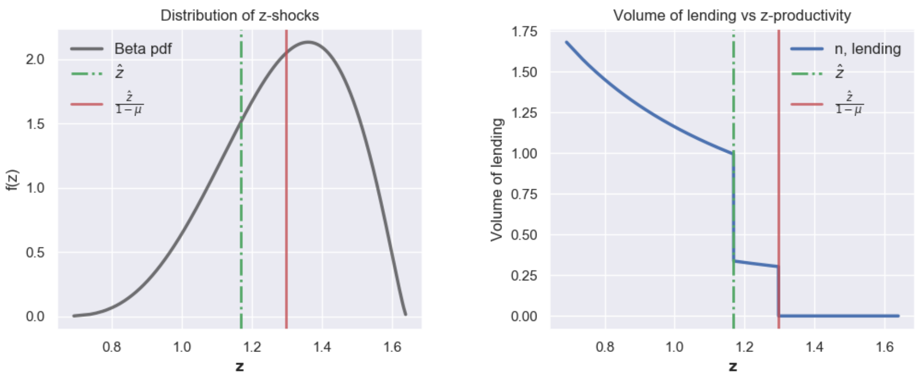
Period	90-06	13-18
spread	1.60	1.68
std	0.27	0.10
rate	5.34	2.10
std	1.23	0.36

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 Model Simulations

C.1 Quantitative Mechanism

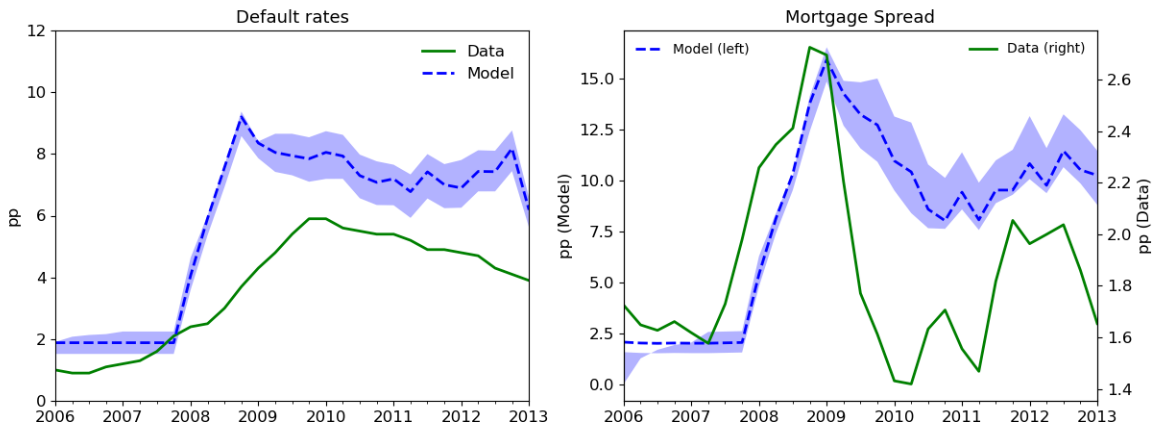
Figure 13: Distribution of lending cost and lending volumes across lenders



The left panel shows the implied density for $F(z)$ on the benchmark calibration. The right panel plots the volume of loan origination to households (y-axis) against the support of lending costs (x-axis).

C.2 The Great Recession

Figure 14: Household aggregates during the Great Recession



Panel a: Data corresponds to the percentage of delinquent mortgage loans 90 days or more, or in foreclousure. Source: National Mortgage Database, FHFA.
Panel b: Data is the flow of residential real estate investment in 2015 prices from the flow of funds. All series are shown as the percentage change with respect to 2006.

C.2.1 Dynamic Panel Estimations

Fluctuations of aggregates in the mortgage market are negatively correlated with fluctuations in households' default risk, which depends on households' fundamentals, namely, fluctuations in the value of the collateral—induced by house prices—and households' income. The model developed in Section 3 captures this negative correlation by endogenously establishing an inverse relationship between the quality of securities and households' default risk.

I perform a dynamic panel data estimation following the methodology in Arellano and Bond (1991) to document that the volumes of mortgage lending at the level of the originating institution are negatively associated with aggregate measures of households default on their mortgage obligations, and households aggregate disposable personal income. Table 15 shows this, I control by asset size and funding costs which have the predicted sign.

Table 15: Arellano-Bond dynamic panel data estimation

Dependent var: log(lending)	
lending vol USD, first lag	0.143^{***}
default rate	-0.037^{***}
10yr TB rate	-0.364^{***}
DPI growth rate	-0.011^{***}
log (assets USD)	0.112^{***}
Number of obs	22,356
Period	1990-2016

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Source: HMDA LARs and Reporter Panel 1990-2016.
Dependent variable is the logarithm of the aggregate volume of lending in USD of 2015 at the level of the mortgage originator. Default rate corresponds to the fraction of single family mortgage loans that are delinquent 90 days or more, or in foreclosure. DPI stands for disposable personal income from NIPA.

Table 16 shows the estimate for the volume of sales at the level of originator against the same measure of aggregate households' default and income, using the same set of controls. HMDA reports the type of purchases of loans in the securitization market, so it is possible to differentiate between sales of loans to the agency segment, Freddie Mac and Fannie Mae, and to other private institutions.

Also, the magnitude and signs of correlations of the volume of sales with respect to all variables are of similar magnitude as those observed for the volume of lending when breaking down the market by segments.

Table 16: Fixed effects, panel regression

Dependent var: log(sales)	Priv segment	Agency segment
default rate	-0.060^{*}	-0.040^{**}
10yr TB rate	-0.436^{***}	-0.405^{***}
DPI growth rate	0.015	-0.052^{***}
log (assets)	0.121^{***}	0.277^{***}
R-sq	0.0717	0.0310
Number of obs	5,163	17,443
Period	1990-2016	1990-2016

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Source: HMDA LARs and Reporter Panel 1990-2016
Dependent variable is the logarithm of the aggregate volume of loan sales in USD of 2015 at the level of the mortgage originator. Default rate corresponds to the fraction of single family mortgage loans that are delinquent 90 days or more, or in foreclosure. DPI stands for disposable personal income from NIPA.

D Computational Algorithm

D.1 Solving the General Equilibrium Model

I solve the model 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, I set a grid of 40 points for $\mathcal{B}$, 40 points for $\mathcal{H}$, and 10 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 $X \in \mathcal{X}$.

I solve the model by global solution methods performing value function iteration to solve and obtain borrowers policy functions, and use the closed form characterization of lender's decision rules to solve for the system of market clearing conditions within the space of aggregate states.

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

D.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 κ is such that:

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

$\kappa > 0$ 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.

The second metric, we evaluate consumption equivalent change for both goods:

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

E Proofs to Lemmas and Propositions

E.1 Derivation of default threshold $\bar{\omega}$

The recursive representation of the representative borrower household problem (4) is:

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

where $\{p_h, q\}$ are the price of housing and the discounted price of credit. We have made an explicit dependence of the household's default threshold $\bar{\omega}$. 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 CDFs 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:

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

aslo, 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 $\{N, H', \bar{\omega}\}$:

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

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 $\tilde{\xi} = \xi/U_c$.

The Envelope Theorem in this case

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

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

$$q = \tilde{\xi} + \beta^B\mathbb{E}\left[\frac{U'_c}{U_c}(1-\lambda(\bar{\omega}'))(q'(1-\phi)+\phi)\right] \tag{24}$$

$$p_h(1-\pi\tilde{\xi}) = \beta^B\mathbb{E}\left[\frac{U'_c}{U_c}\left((1-\lambda(\bar{\omega}'))\mu_\omega(\bar{\omega}')p'_h + \frac{U'_H}{U'_C}\right)\right] \tag{25}$$

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:

$$\begin{aligned} U_c(-\bar{\omega}g_\omega(\bar{\omega})p_hH + g_\omega(\bar{\omega})\phi B) + \tilde{\xi}(1-\phi)g_\omega(\bar{\omega})B &= -\beta^B\mathbb{E}\left[\frac{\partial V}{\partial B'}\frac{\partial B'}{\partial\bar{\omega}}\right] \\ U_c g_\omega(\bar{\omega})(-\bar{\omega}p_hH + \phi B) + U_c\tilde{\xi}(1-\phi)g_\omega(\bar{\omega})B &= \beta^B\mathbb{E}\left[\frac{\partial V}{\partial B'}(1-\phi)g_\omega(\bar{\omega})B\right] \\ U_c g_\omega(\bar{\omega})(-\bar{\omega}p_hH + \phi B + \tilde{\xi}(1-\phi)B) &= (1-\phi)g_\omega(\bar{\omega})B\left[\beta^B\mathbb{E}[V_{B'}]\right] \\ U_c g_\omega(\bar{\omega})(-\bar{\omega}p_hH + \phi B + \tilde{\xi}(1-\phi)B) &= -(1-\phi)g_\omega(\bar{\omega}_h)BU_c(q-\tilde{\xi}) \\ -\bar{\omega}p_hH + \phi B &= -(1-\phi)Bq \\ \bar{\omega} &= \frac{B}{p_hH}[\phi + (1-\phi)q] \end{aligned} \tag{26}$$

E.2 Proof of Lemma 1

1. Assumptions: i) lender holds one asset: budget set is linear in b. ii) homothetic preferences, $u(c) = \log(c)$, imply:
   (a) policy functions are linear in b: $c(z, b, X), b'(z, b, X), s_G(z, b, X), s_B(z, b, X), d(z, b, X)$
2. By assumption lender's idiosyncratic origination costs are assumed identical and independently distributed across lenders and across time.[42] Independence across lenders implies that the joint distribution of debt holdings and idiosyncratic shocks $\Gamma(b, z)$ at time t can be integrated using the individuals' 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 $\{\sigma_{\omega t}, Y_t\}$.
3. For given $\{p, \mu\}$: aggregates S_G, S_B, D do not depend on the distribution of b. See additional derivations E.13.
4. Therefore, neither do market clearing values $p_t,\ q_t,\ \mu_t$. See additional derivations E.13.
5. Thus, it is not necessary to know the distribution Γ to compute aggregate quantities and prices. B is a sufficient statistic.

E.3 Proof of Lemma 2

1. Taking portfolio lending decisions b' as given, the problem of lender j, equation (10), consists of maximizing consumption c by choosing $\{n, s_G, s_B, d\}$, which implies solving a linear problem. To see this, combine a lender's budget constraint (7) and the portfolio's law of motion (6), which yields

$$c = (1 - \lambda(\bar{\omega}))b\,[\phi + (1-\phi)z\tilde{q}] + s_B\ p + s_G\,[p(1-\tau) - z\tilde{q}] - d\,[p - z\tilde{q}(1-\mu)] - z\tilde{q}b'.$$

where $\tilde{q}$ is the discounted price of lending including the government origination fee, as introduced in (11). Since each lender j takes as given prices and the adverse selection discount: $\{p, \tilde{q}, \mu\}$, trading decisions are derived by comparing static payoffs. For sales of low-quality loans s_B: if $p > 0$ a lender has no incentive to keep a low-quality loan with high probability of zero recovery value. She chooses to sell all of them, hitting the corner in (9): $s_B = (1-\phi)\lambda(\bar{\omega})b$. The decision to sell good-outstanding loans s_G is based on how a lender's origination cost $\tilde{q}z$ compares with the price of selling loans p. Taking into account the portfolio constraint in (8) yields:

$$s_G = \begin{cases} (1-\lambda(\bar{\omega}))(1-\phi)b & \text{if} \quad z < \frac{p}{\tilde{q}} \\ 0 & \text{if} \quad z \geq \frac{p}{\tilde{q}} \end{cases}$$

The decision to purchase securities d depends on how a lender's origination cost $\tilde{q}z$ compares with the effective cost of buying a security $\frac{p(1-\tau)}{1-\mu}$. Notice, a lender understands that she

[42] 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.

is buying a bundle of all the loans supplied in the securitization market, and because all participants have incentives to sell all their low-quality loans, a fraction μ of them default with a zero payoff. Consequently, the effective cost of buying securities taking into account the subsidy to buyers, $\frac{p(1-\tau)}{1-\mu}$, is at least as high as the market price p:

$$d = \begin{cases} > 0 & \text{if} \quad z > \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu} \\ 0 & otw \end{cases}$$

2. Given a lender's draw of origination cost $z \in [z_a, z_b]$, her trading decisions can be characterized according to cutoffs $\{\frac{p}{\tilde{q}}, \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}\}$. We define three types:

   - Seller. For a lender j that such that $z \in [z_{a,} p/\tilde{q})$, trading decisions are: $\{d = 0,\ s_G = (1-\lambda(\bar{\omega}))(1-\phi)b,\ s_B = \lambda(\bar{\omega})(1-\phi)b\}$. By replacing these policy functions in (6) obtains the origination decision for a seller: $n = b'$.
   - Buyer. For a lender j such that $z \in (\frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}, z_b]$, trading decisions are $\{d > 0,\ s_G = 0,\ s_B = \lambda(\bar{\omega})(1-\phi)b\}$. Notice that n and d are alternative ways of lending resources. Originating one loan today costs $z\tilde{q}$ while purchasing a security today costs p. Given that $z > \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}$, the optimal decision is to set $n = 0$. Replacing these decisions in (6) yields the policy function for purchases $d = \frac{b'-(1-\phi)(1-\lambda(\bar{\omega}))b}{1-\mu}$.
   - Holder. For a lender j such that $z \in [\frac{p}{\tilde{q}},\ \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}]$, trading decisions are $\{d = 0,\ s_G = 0,\ s_B = \lambda(\bar{\omega})(1-\phi)b\}$. Replacing these decisions in (6) obtains $n = b' - (1-\lambda(\bar{\omega}))(1-\phi)b$.

3. If there is no positive price that clears supply and demand, the securitization market will not be active. Trading decisions for all lenders are trivial: $\{d = 0,\ s_G = 0,\ s_B = 0\}$. Replacing these decisions in the law of motion of debt holdings, equation (6), obtains the origination decision: $n = b' - (1-\lambda(\bar{\omega}))(1-\phi)b$.

E.4 Proof of Lemma 3

To develop this proof first, we define a lender's wealth function that relaxes a lender's original budget set to a convex budget set. The second part consist in deriving the consumption-savings rule.

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

$$W(b, z; X) = b\left[(1-\lambda(\bar{\omega}))\phi + \lambda(\bar{\omega})(1-\phi)p + (1-\lambda(\bar{\omega}))(1-\phi)\tilde{q}\max\{p/\tilde{q}, \min\{z, \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}\}\}\right]. \quad (27)$$

   The virtual wealth represents a lender's consolidated wealth as a generic function of her origination cost z, prices $\{\tilde{q}, p\}$, and lending and trading decisions $\{n, d, s_G, s_B\}$. It consolidates the lender's sources income: cash payments from her maturing portfolio, cash from selling low-quality loans, and the virtual valuation of her outstanding portfolio of loans—at either the market price or at the lender's internal valuation rate. Using (27) we can define a convex budget set that is weakly larger than the original budget set in problem (10). The problem of a lender under this relaxed budget set is given by

$$
\begin{aligned}
V(b,z;X) &= \max_{\{c,b'\}} \log(c) + \beta^L \mathbb{E}_{X'|X} V(b',z';X') \qquad (28)\\
s.t. & \\
& c + b'\tilde{q}\min\{z, \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}\} \leq W(b,z;X).
\end{aligned}
$$

2. We will derive $\{c, b'\}$ policy functions by guess and verify. Taking First Order Conditions w.r.t to b' to program (28) obtains:

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

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 out of increasing stock of loans in one unit. Given that assumption of log-preferences:

$$
\frac{1}{c}\tilde{q}\min\{z, \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}\} = \beta^L \mathbb{E}_{X'|X}\left[\frac{1}{c'}W_{b'}(b',z';X')\right]
$$

Guess that the policy function for consumption has the form: $c = \alpha W(b,z;X)$, where $\alpha \in (0,1)$. Then, from budget set in (28) :

$$
b' = \frac{(1-\alpha)W(b,z;X)}{\tilde{q}\min\{z, \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}\}}
$$

and

$$
\begin{aligned}
c' &= \alpha W(b',z';X')\\
&= \alpha W_{b'}(b',z';X')b'\\
&= \alpha W_{b'}(b',z';X')\left[\frac{(1-\alpha)W(b,z;X)}{\tilde{q}\min\{z, \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}\}}\right]
\end{aligned}
$$

Replacing expression for c' in the Euler equation obtains:

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

which yields the consumption and lending policy functions:

$$
\begin{aligned}
c &= (1-\beta^L)W(b,z;X)\\
b' &= \frac{\beta^L}{\tilde{q}\min\{z, \frac{p}{\tilde{q}}\frac{1-\tau}{1-\mu}\}}W(b,z;X).
\end{aligned}
$$

E.5 Proof of Lemma 4

Suppose there is a lender 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 $b' < (1-\lambda(\bar{\omega}))(1-\phi)b$ 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 $D = 0$.

E.6 Proof of Lemma 5

If there is a $p > 0$ that clears the securitization market, by Lemma 2 the policy function of lenders with origination costs below the second equilibrium cut-off imply a strictly positive amount of new loan issuance, see Lemma 2. Hence, the last marginal lender to issue new loans is such that $z \leq \frac{p}{q}\frac{1-\tau}{1-\mu}$ and the right hand side determines the cut-off $\bar{z}$.

Instead, whenever the price that clears the securitization market is given by $p = 0$, the virtual wealth function of the lender reduces to $W = b\left[(1-\lambda(\bar{\omega}))\phi + (1-\lambda(\bar{\omega}))(1-\phi)zq\right]$. Using the optimal saving policy function in Lemma 3 the policy function of new loan issuance for lenders becomes $n = \frac{\beta^L}{zq}b(1-\lambda(\bar{\omega}))\phi - (1-\beta^L)(1-\lambda(\bar{\omega}))(1-\phi)b$. Then, we can derive the upper bound for a lender's origination cost z so that a lenders issues a strictly positive amount of new loans

$$\begin{gathered} n > 0 \\ \frac{\beta^L \phi}{(1-\beta^L)(1-\phi)}\frac{1}{q} > z \end{gathered}$$

the left hand side determines the cut-off $\bar{z}$ when the price of securities in the securitization market is zero. 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.

E.7 Proof of Lemma 6

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 $\bar{\omega} = \frac{B_{ss}}{pH_{ss}}(\phi + (1-\phi)q_{ss})$. Then, ceteris paribus, given that the increase in housing volatility is by a mean preserving spread it follows that: $\lambda(\bar{\omega}) \leq \lambda'(\bar{\omega})$.

E.8 Proof of Lemma 7

Lemma 7 establishes that the adverse selection discount μ is increasing in borrowers default rate $\lambda(\bar{\omega})$ and decreasing in the securitization market cut-off $\hat{z}$.

1. by definition

$$\begin{aligned} \mu(\lambda, \hat{z}) &= \frac{S_B(\hat{z})}{S(\hat{z})} \\ &= \frac{\int_{z_a}^{z_b} \lambda(\bar{\omega})(1-\phi)b\ d\Gamma(z,b)}{S_B(\hat{z}) + S_G(\hat{z})} \\ &= \frac{\lambda(\bar{\omega})(1-\phi)B}{\lambda(\bar{\omega})(1-\phi)B + \int_{z_a}^{\hat{z}} s_G dF} \\ &= \frac{\lambda(\bar{\omega})}{\lambda(\bar{\omega}) + (1-\lambda(\bar{\omega}))F(\hat{z})} \end{aligned}$$

where the last equality using: $s_G = (1-\lambda(\bar{\omega}))(1-\phi)b$. F is the CDF of z.

2. for a given cut-off $\hat{z}$, consider an increase in the default rate arising from higher housing volatility. In Lemma 6 we established that $\lambda(\bar{\omega}) \leq \lambda'(\bar{\omega})$. Then, using the definition we want to show that:

$$\mu(\lambda', \hat{z}) \geq \mu(\lambda, \hat{z})$$
$$\frac{\lambda'(\bar{\omega})}{\lambda'(\bar{\omega}) + (1 - \lambda'(\bar{\omega}))F(\hat{z})} \geq \frac{\lambda(\bar{\omega})}{\lambda(\bar{\omega}) + (1 - \lambda(\bar{\omega}))F(\hat{z})}$$
$$\lambda'(\bar{\omega})[\lambda(\bar{\omega}) + (1 - \lambda(\bar{\omega}))F(\hat{z})] \geq \lambda(\bar{\omega})[\lambda'(\bar{\omega}) + (1 - \lambda'(\bar{\omega}))F(\hat{z})]$$
$$\frac{\lambda'(\bar{\omega})}{\lambda(\bar{\omega})}\frac{(1 - \lambda(\bar{\omega}))}{(1 - \lambda'(\bar{\omega}))} \geq 1$$

which is satisfied.

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

A corollary of Lemma 7 is that under an appropriate assumption on the density of lender's costs distribution $F(z)$, we can guarantee that the second cutoff moves in the opposite direction to the first cutoff.

Corollary. Under Assumption A1, the second equilibrium cutoff $\frac{\hat{z}}{1-\mu(\hat{z})}$ *is decreasing in* $\hat{z}$.

Assumption A1: $\forall\ \hat{z} \in [z_a, z_b]$:

$$m(\hat{z}) > \frac{1}{\hat{z}}\left[1 + \frac{1-\lambda}{\lambda}F(\hat{z})\right]$$

where $m(\hat{z}) = \frac{f(\hat{z})}{F(\hat{z})}$ *is the inverse Mills ratio of* $\hat{z}$.

As securitization market conditions improve the cutoff that indicates the real price paid by buyers gets closer to first cutoff, in other words, the private information wedge become lower.

To derive the condition needed, first, conjecture that exist a market cut-off $\hat{z}$ that satisfies $A1$, then we want the ratio $\frac{\hat{z}}{1-\mu(\hat{z})}$ to be decreasing in $\hat{z}$, i.e. for $\frac{\partial \cdot}{\partial \hat{z}} < 0$ to hold it must be that:

$$\frac{1}{\hat{z}}\left(1 + \frac{1-\lambda}{\lambda}F(\hat{z})\right) < m(\hat{z})$$

where $m(\hat{z}) = \frac{f(\hat{z})}{F(\hat{z})}$ is the inverse mills ratio of $\hat{z}$.

E.9 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, I derive the analytical expression for each discounted price and then verify the inequality.

In steady state the demand for new loans in primary market is given by

$$N_{ss}^D = B_{ss}(1 - (1 - \phi)(1 - \lambda(\bar{\omega}_{ss})))$$

Under complete information low-quality loans are not traded since all lenders can easily identify them and their payoff is zero. If lenders have access to a securitization market, their consumption, saving and trading decisions can be derived in similar fashion to Lemma 2. In this case, there is only one cutoff $\bar{z} \equiv \frac{p}{q}$. 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:

$$\begin{aligned} N_{ss}^{S} &= \int_{z_a}^{\bar{z}} n^{CI}(b,z;X)d\Gamma(b,z) \\ &= B_{ss}\frac{\beta^L}{q_{ss}^{CI}}(1-\lambda(\bar{\omega}_{ss}))(\phi+p(1-\phi))\int_{z_a}^{\bar{z}} \frac{1}{z}dFz \\ &= B_{ss}\frac{\beta^L}{q_{ss}^{CI}}(1-\lambda(\bar{\omega}_{ss}))\phi\int_{z_a}^{\bar{z}} \frac{1}{z}dFz + B_{ss}\beta^L(1-\lambda(\bar{\omega}_{ss}))\bar{z}(1-\phi)\int_{z_a}^{\bar{z}} \frac{1}{z}dFz \end{aligned}$$

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

$$\begin{aligned} q_{ss}^{CI} &= \frac{\beta^L(1-\lambda(\bar{\omega}_{ss}))\phi\int_{z_a}^{\bar{z}}\frac{1}{z}dFz}{(1-(1-\phi)(1-\lambda(\bar{\omega}_{ss}))-\beta^L(1-\lambda(\bar{\omega}_{ss}))\bar{z}(1-\phi)\int_{z_a}^{\bar{z}}\frac{1}{z}dFz} \\ &= \frac{\beta^L\phi\int_{z_a}^{\bar{z}}\frac{1}{z}dFz}{(1-\phi)\left[\frac{1}{(1-\lambda(\bar{\omega}_{ss}))(1-\phi)}-1-\beta^L\bar{z}\int_{z_a}^{\bar{z}}\frac{1}{z}dFz\right]} \end{aligned} \tag{29}$$

If lenders do not have access to a securitization market their decisions can be derived directly from Lemma 2. In steady state the aggregate credit supply is given by:

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

w.l.o.g we assume $z_b \geq \frac{\beta^L\phi}{(1-\beta^L)(1-\phi)}$. Then, using market clearing condition for the primary market we can derive an expression for the discounted price of new mortgage debt in steady state:

$$\begin{aligned} q_{ss}^{NSM} &= \frac{\beta^L(1-\lambda(\tilde{\omega}_{ss}))\phi\int_{z_a}^{z_b}\frac{1}{z}dFz}{1-\beta^L(1-\lambda(\tilde{\omega}_{ss}))(1-\phi)} \\ &= \frac{\beta^L\phi\int_{z_a}^{z_b}\frac{1}{z}dFz}{(1-\phi)\left[\frac{1}{(1-\lambda(\tilde{\omega}_{ss}))(1-\phi)}-\beta^L\right]} \end{aligned} \tag{30}$$

The last step consist in comparing equations (29) and (30). Notice that for any $\bar{z} \in [z_a, z_b)$ the numerators satisfy

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

Also, notice that in steady state, the household default threshold in (26) becomes $\omega_{ss} = \pi(\phi+(1-\phi)q_{ss})$, hence, a generic default function is $\lambda(\omega_{ss}) = G(\pi(\phi+(1-\phi)q_{ss}))$ where G is the CDF of the household's stochastic housing shocks. Suppose by contradiction that $q_{ss}^{NSM} > q_{ss}^{CI}$. Then, the denominators in (29) and (30) must satisfy:

$$
\begin{aligned}
\frac{1}{(1-\lambda(\bar{\omega}_{ss}))(1-\phi)} - 1 - \beta^L \bar{z} \int_{z_a}^{\bar{z}} \frac{1}{z} dFz &> \frac{1}{(1-\lambda(\tilde{\omega}_{ss}))(1-\phi)} - \beta^L \\
\frac{\lambda(\bar{\omega}_{ss}) - \lambda(\tilde{\omega}_{ss})}{(1-\lambda(\bar{\omega}_{ss}))(1-\lambda(\tilde{\omega}_{ss}))} &> (1-\phi)\left[1 + \beta^L \left(\bar{z}\int_{z_a}^{\bar{z}} \frac{1}{z} dFz - 1\right)\right]
\end{aligned}
$$

where given that $\beta^L < 1, \phi > 0$, and $\bar{z}\int_{z_a}^{\bar{z}} \frac{1}{z} dFz > 0$ the right-hand-side is always positive, i.e. $\frac{1}{\beta^L} + \bar{z}\int_{z_a}^{\bar{z}} \frac{1}{z} dFz > 1$. Then, $q_{ss}^{NSM} > q_{ss}^{CI}$ yields $\lambda(\bar{\omega}_{ss} \equiv \pi(\phi + (1-\phi)q_{ss}^{CI})) < \lambda(\tilde{\omega}_{ss} \equiv \pi(\phi + (1-\phi)q_{ss}^{NSM})$ since G is a strictly increasing function. Implying a negative left-hand-side, which is a contradiction. Hence, it is the case that $q_{ss}^{CI} > q_{ss}^{NSM}$ as stated in Proposition 1.

E.10 Proof of Proposition 2

The condition for a market crash is derived from the aggregate demand of securities, see Subsection E.13. In steady state we have:

$$
\begin{aligned}
D &= \int d(b, z; X)\ d\Gamma(b, z) \\
&= \frac{1 - F\left(\hat{z}\frac{(1-\tau)}{(1-\mu)}\right)}{1-\mu} B \left[\frac{\beta^L}{z^m}[(1-\lambda(\bar{\omega}))(\phi + (1-\phi)z^m) + \lambda(\bar{\omega})(1-\phi)p] - (1-\lambda(\bar{\omega}))(1-\phi)\right] \\
&= \frac{1 - F\left(\hat{z}\frac{(1-\tau)}{(1-\mu)}\right)}{p(1-\tau)} B \left[\beta^L(1-\lambda(\bar{\omega}))\phi - \frac{p(1-\tau)}{(1-\mu)}(1-\beta^L)(1-\lambda(\bar{\omega}))(1-\phi)\right] \\
&\quad + \frac{\beta^L}{p(1-\tau)} \underbrace{p\lambda(\bar{\omega})(1-\phi)B\left[1 - F\left(\hat{z}\frac{(1-\tau)}{(1-\mu)}\right)\right]}_{S_B^{\text{buyers}}}
\end{aligned}
$$

where S_B^{buyers} denotes the supply of low-quality loans from lenders that buy securities and we use the definition $z^m = p(1-\tau)/(1-\mu)$. Notice that if $D < S_B^{\text{buyers}}$ then there cannot be a positive price clearing the securities market. Rearranging the expression in the large bracket of the first term in the last equation above, yields a sufficient condition for the securities market not to be active:

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

Item 1 in Proposition 2 follows directly from the condition derived above and from the characterization of lenders policy functions for the case in which the securities market is not active, i.e. when Lemma 4 is not satisfied. For Item 2, notice that we established in Lemma 2 that under private information, if there is a positive equilibrium price in the securitization market, the second cutoff satisfies: $\hat{z} < \hat{z}\frac{1-\tau}{1-\mu}$, i.e. in any equilibrium outcome under private information there is a positive wedge given by the distance between both cutoffs. This implies that any equilibrium price of debt under private information, q^*, must satisfy: $q^* < q^{CI}$. Also, notice that an economy without securitization market features zero reallocation of resources among lenders and hence the highest possible intermediation cost, which implies: $q^{NSM} < q^*$.

Notice that this condition is independent of the support of the density of origination costs $[z_a, z_b]$, which defines the range of feasible equilibrium cutoffs for the model. In general, the RHS term of the market collapse condition defines the value of the origination cost of the last marginal lender that is willing to participate in the credit market. For the calibration performed in the quantitative section 5, this feasibility cutoff is larger than the calibrated upper bound, i.e $z_b > \frac{\beta^L \phi}{(1-\beta^L)(1-\phi)}$, thus the relevant market failure sufficient condition is $\min_p \left\{ \frac{p(1-\tau)}{(1-\mu)} \right\} > z_b$.

E.11 Proof of Proposition 3

The proof consists in showing 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 $\{p^{CI}, q^{CI}\}$:

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

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

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

Notice that between an economy with private information and an economy with complete information, prices satisfy: $\frac{p^{AI}}{q^{AI}} \leq \frac{p^{CI}}{q^{CI}}$, 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, market prices also satisfy $\frac{p^{FS}}{q^{FS}} \leq \frac{p^{CI}}{q^{CI}}$. Then, it follows that the mass of buyers satisfies $1 - F\left(\frac{p^{FS}}{q^{FS}}\right) \geq 1 - F\left(\frac{p^{CI}}{q^{CI}}\right)$. Also, notice that $1/(1-\mu) > 1$ as the adverse selection discount is always strictly positive even with a full subsidy. Wlog we assume the steady state amount of debt is the same in both economies. It remains to check that the expression in the square bracket from D^{FS} is larger than its counterpart in D^{CI}, working the inequality obtains the following condition:

$$\beta^L \lambda^{FS}(1-\phi)p^{FI} + (1-\beta^L)(1-\phi)(\lambda^{FS} - \lambda^{CI}) + \beta^L \phi \left(\frac{1-\lambda^{FS}}{p^{FS}} - \frac{1-\lambda^{CI}}{p^{CI}}\right) \geq 0$$

The households default function is given by $\lambda \equiv G(\pi_{ss}(\phi + (1-\phi)q^*))$ where G is the CDF of households housing shocks. By proposition 1, we know that $q^{AI} \in (q^{NSM}, q^{CI})$ in the absence of policy. However, introducing a guarantee fee $\gamma > 0$ as in $q^{AI} = q^* + \gamma$, see (11), distorts the price q^* faced by borrowers. The above condition is always satisfied for a large range of the parameters given by the calibration in section 5, as the first term is substantially larger than the rest.

E.12 Proof of Proposition 4

First, in Lemma 6 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, if Lemma 4 is satisfied, item 1 follows from Lemma 7. Second, by the corollary in Lemma

7 the second cutoff will increase when the adverse selection discount increases. By the definition of the aggregate demand of securities, equation (20), 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 resources (cash in hand) 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.

E.13 Additional derivations

For Proof of Lemma 1

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

   (a) Aggregate Supply of loans, S

$$\begin{aligned}
S &= S_B + S_G \\
&= \int s_B(b, z; X)\ d\Gamma(b, z) + \int s_G(b, z; X)\ d\Gamma(b, z) \\
&= \int_z \int_b s_B(b, z; X)\ dG(b)dF(z) + \int_z \int_b s_G(b, z; X)\ dG(b)dF(z) \\
&= \int_z \int_b \lambda(\bar{\omega})(1-\phi)b\ dG(b)dF(z) + \int_z \int_b (1-\lambda(\bar{\omega}))(1-\phi)b\ dG(b)dF(z) \\
&= \lambda(\bar{\omega})(1-\phi) \int_{z_a}^{z_b} \left[\int_b bdG(b)\right] dF(z) + (1-\lambda(\bar{\omega}))(1-\phi) \int_{z_a}^{p/q} \left[\int_b bdG(b)\right] dF(z) \\
&= \lambda(\bar{\omega})(1-\phi) \int_{z_a}^{z_b} BdF(z) + (1-\lambda(\bar{\omega}))(1-\phi) \int_{z_a}^{p/q} BdF(z) \\
&= B(1-\phi) \left[\lambda(\bar{\omega}) \int_{z_a}^{z_b} dF(z) + (1-\lambda(\bar{\omega})) \int_{z_a}^{p/q} dF(z)\right] \\
&= B(1-\phi) \left[\lambda(\bar{\omega}) + (1-\lambda(\bar{\omega}))F(p/q)\right]
\end{aligned}$$

   (b) Aggregate Demand of securities, D

$$\begin{aligned}
D &= \int d(b, z; X)\ d\Gamma(b, z) \\
&= \int_z \int_b d(b, z; X)\ dG(b)dF(z) \\
&= \int_{z^m/q}^{z_b} \int_b \frac{b' - (1-\lambda(\bar{\omega}))(1-\phi)b}{1-\mu}\ dG(b)dF(z) \\
&= \frac{1}{1-\mu}\left[\int_{z^m/q}^{z_b} \int_b b'\ dG(b)dF(z) - (1-\lambda(\bar{\omega}))(1-\phi) \int_{z^m/q}^{z_b} \int_b b\ dG(b)dF(z)\right] \\
&= \frac{1}{1-\mu}\left[\int_{z^m/q}^{z_b} \frac{\beta}{z^m} \left((1-\lambda(\bar{\omega}))\phi + \lambda(\bar{\omega})(1-\phi)p + (1-\lambda(\bar{\omega}))(1-\phi)z^m\right) BdF(z)\right]
\end{aligned}$$

$$
\begin{aligned}
& -\frac{1}{1-\mu}(1-\lambda(\bar{\omega}))(1-\phi)B\int_{z^m/q}^{z_b} dF(z) \\
= & \frac{1-F(z^m/q)}{1-\mu}B\left[\frac{\beta}{z^m}[(1-\lambda(\bar{\omega}))(\phi+(1-\phi)z^m)+\lambda(\bar{\omega})(1-\phi)p]-(1-\lambda(\bar{\omega}))(1-\phi)\right]
\end{aligned}
$$

where $z^m = \frac{p(1-\tau)}{1-\mu(p,q)}$. It follows that the market clearing values of $\{p,\mu\}$ do not depend on the distribution of b either.

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 meaning $p > 0$,

$$
\begin{aligned}
N^{\text{seller}} &= \int n(b,z;X)d\Gamma(b,z) \\
&= \int_{z_a}^{p/q}\int_b b'(b,z;X)\; dG(b)dF(z) \\
&= \int_{z_a}^{p/q}\frac{\beta}{zq}\left[(1-\lambda(\bar{\omega}))\phi+(1-\phi)p\right]\left[\int_b b\; dG(b)\right]dFz \\
&= B\frac{\beta}{q}\left[(1-\lambda(\bar{\omega}))\phi+(1-\phi)p\right]\int_{z_a}^{p/q}\frac{1}{z}dFz \\
N^{\text{holder}} &= \int n(b,z;X)d\Gamma(b,z) \\
&= \int_p^{z^m/q}\int_b \left[b'(b,z;X)-(1-\lambda(\bar{\omega}))(1-\phi)b\right]\; dG(b)dF(z) \\
&= \int_p^{z^m/q}\frac{\beta}{zq}\left[(1-\lambda(\bar{\omega}))\phi+\lambda(\bar{\omega})(1-\phi)p+(1-\lambda(\bar{\omega}))(1-\phi)zq\right]\left[\int_b b\; dG(b)\right]dFz \\
&\quad -\int_p^{z^m/q}(1-\lambda(\bar{\omega}))(1-\phi)\left[\int_b b\; dG(b)\right]dFz \\
&= B\frac{\beta}{q}\left[(1-\lambda(\bar{\omega}))\phi+\lambda(\bar{\omega})(1-\phi)p\right]\int_p^{z^m/q}\frac{1}{z}dFz+\beta(1-\lambda(\bar{\omega}))(1-\phi)B\int_p^{z^m/q}dFz
\end{aligned}
$$

$$
\begin{aligned}
& -(1-\lambda(\bar{\omega}))(1-\phi)B\int_{p}^{z^m/q} dFz \\
= \; & B\frac{\beta}{q}\left[(1-\lambda(\bar{\omega}))\phi+\lambda(\bar{\omega})(1-\phi)p\right]\log(z)f(z)|_{p}^{z^m/q} \\
& -B(1-\beta)(1-\lambda(\bar{\omega}))(1-\phi)\left(F(z^m/q)-F(p/q)\right) \\
N^L = \; & N^{\text{seller}}+N^{\text{holder}}
\end{aligned}
$$

The case when there is no trade in securitization markets (or alternatively all assets trade at $p=0$) and each lender originates loans using its own technology.

$$
\begin{aligned}
N^L &= \int n(b,z;X)d\Gamma(b,z) \\
&= \int_{z_a}^{z_b}\int_{b}\left[b'(b,z;X)-(1-\lambda(\bar{\omega}))(1-\phi)b\right] \; dG(b)dF(z) \\
&= \int_{z_a}^{z_b}\frac{\beta}{zq}\left[(1-\lambda(\bar{\omega}))\phi+(1-\lambda(\bar{\omega}))(1-\phi)zq\right]\left[\int_{b} b \; dG(b)\right]dF(z) \\
&\quad -\int_{z_a}^{z_b}(1-\lambda(\bar{\omega}))(1-\phi)\left[\int_{b} b \; dG(b)\right]dFz \\
&= B(1-\lambda(\bar{\omega}))\left[\frac{\beta}{q}\phi\int_{z_a}^{z_b}\frac{1}{z}dF(z)-(1-\beta^L)(1-\phi)\right]
\end{aligned}
$$

Budget sets by type of lender

Replacing the optimal origination and trading decisions of Lemma 2 in the budget constraint and in the law of motion of lenders, problem (10), obtains:

- Buyers:

$$
c+p(1-\tau)\left[\frac{b'-(1-\lambda(\bar{\omega}))(1-\phi)b}{1-\mu}\right]=(1-\lambda(\bar{\omega}))\phi b+\lambda(\bar{\omega})(1-\phi)pb
$$

$$
c+z^m b'=\left[(1-\lambda(\bar{\omega}))\phi+\lambda(\bar{\omega})(1-\phi)p+(1-\lambda(\bar{\omega}))(1-\phi)z^m\right]b
$$

  where $z^m=p(1-\tau)/(1-\mu)$.

- Sellers:

$$
c+zq\left[b'\right]=(1-\lambda(\bar{\omega}))\phi b+\lambda(\bar{\omega})(1-\phi)pb+(1-\lambda(\bar{\omega}))(1-\phi)pb
$$

$$
c+zqb'=\left[(1-\lambda(\bar{\omega}))\phi+(1-\phi)p\right]b
$$

- Holder:

$$
c+zq[b'-(1-\lambda(\bar{\omega}))(1-\phi)b]=(1-\lambda(\bar{\omega}))\phi b+\lambda(\bar{\omega})(1-\phi)pb
$$

$$
c+zqb'=\left[(1-\lambda(\bar{\omega}))\phi+\lambda(\bar{\omega})(1-\phi)p+(1-\lambda(\bar{\omega}))(1-\phi)zq\right]b
$$

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