Leverage and the Foreclosure Crisis*

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Abstract

How much of the foreclosure crisis can be explained by the large number of high-leverage mortgages originated during the housing boom? In our model, heterogeneous households select from mortgages with different downpayments and choose whether to default given income and housing shocks. The use of low-downpayment loans is initially limited by payment-to-income requirements but becomes unrestricted during the boom. The model approximates key housing and mortgage market facts before and after the crisis. A counterfactual experiment suggests that the increased number of high-leverage loans originated prior to the crisis can explain over 60% of the rise in foreclosure rates.

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1 Introduction

The share of high-leverage loans in mortgage originations started rising sharply in the late 1990s.[1] Pinto (2010, see Figure 1) calculates that among purchase loans insured by the Federal Housing Administration (FHA) or purchased by Government Sponsored Enterprises (GSEs) the fraction of originations with cumulative leverage in excess of 97% of the home value was under 5% in 1990 but rose to almost 40% in 2007. Gerardi et. al (2008) present similar evidence using a dataset of mortgages sold into mortgage-backed securities marketed as "subprime." Among these subprime loans, transactions with a cumulative loan-to-value (CLTV)[2] of 90% or more represented just 10 percent of all originations in 2000 but exceeded 50% of originations in 2006.[3]

Better access to loans with low downpayments made it possible for more households to obtain the financing necessary to purchase a house. At the same time however, because these contracts are characterized by little equity early in the life of the loan, they are prone to default when home prices fall. Not surprisingly then, (see, again, Gerardi et al., 2008, Figure 4, or Mayer et. al., 2009, among many others) mortgages issued during the recent housing boom with high leverage have defaulted at much higher frequency than other loans since home prices began their collapse in late 2006.

How much of the post-2006 rise in foreclosures can be attributed to the increased originations of high-leverage mortgages during the housing boom? To answer this question, we describe a housing model where the importance of high-leverage loans for default rates can be measured. When purchasing a home, households choose between two types of fixed rate

[1]As Foote et al. (2012, section 2) among others point out, high-leverage loans are not new in the United States. Our paper is about the fact that their frequency increased in the years leading up to the foreclosure crisis.

[2]The CLTV at origination is the sum of the face value of all loans secured by the purchased property divided by the purchase price.

[3]Mayer et al. (2009) among others discuss similar evidence. These studies also point out that the use of secondary "piggy-back" loans increased markedly during that period. See also Duca et. al. (2011) and Bokhari et. al. (2013). Loans with non-traditional amortization features such as interest-only phases and balloon payments also became more prevalent during the boom. In an earlier version of this paper (see Corbae and Quintin, 2010), we argue that delayed amortization features have little impact on the foreclosure spike generated by our model.

mortgages: a contract with a 20% downpayment and a contract with no downpayment. Mortgage holders can terminate their contract before maturity either by selling their house or by choosing to default. Foreclosures are costly for lenders because of the associated transaction costs and because they typically occur when home equity is negative. As a result, intermediaries demand higher yields from agents whose asset and income position make foreclosure more likely. In fact, intermediaries do not issue loans to some agents because expected default losses are too high. In particular, our model is consistent with the fact that agents at lower asset and income positions are less likely to become homeowners, face more expensive borrowing terms, and are more likely to default on their loan obligations.

We approximate the course of events depicted in Figures 1 and 2 using a three-stage experiment. The first stage is a long period of moderate real house prices with “tight” approval standards that lasts until the late 1990s. Between 1998 and 2006, approval standards are relaxed and, at the same time, aggregate home prices rise. In 2007, aggregate home prices and approval standards return to their pre-boom level. We think of the beginning of this last stage as the crisis period.

We model changes in approval standards as exogenous changes in payment-to-income (PTI) requirements. A version of our model calibrated to capture key features of pre-boom US housing markets predicts that, following the relaxation of approval standards, the use of low-downpayment mortgages endogenously exceeds 25% at the onset of the crisis, which is in line with the evidence displayed in Figure 1. Likewise, home-ownership rates rise markedly as new households gain access to mortgage markets.

The aggregate home price collapse that takes place at the end of the boom stage in our model causes default rates to increase by 275% above their pre-boom level, slightly over-accounting (by 7%) the corresponding rise in the data. In a counterfactual experiment where PTI requirements are left unchanged throughout the experiment, the use of high-downpayment loans changes little during the boom, and default rates only rise by 105%. This suggests that relaxed approval standards account for 62% of the rise in foreclosures. Importantly, despite the fact that relaxed approval standards account for a large part of the foreclosure crisis, loans are priced taking these standards into account so there are not mispricing issues. Our results say that even with fully rational expectations, the large aggregate home value correction that took place in late 2007 was enough to generate a default spike of a magnitude quite similar to what transpired.

What is the economic mechanism behind our results? In our model, the increased use of low-downpayment loans magnifies the effect of the home price correction for two fundamental reasons. First and most obviously, more households find themselves in negative equity territory following the aggregate shock since average equity levels are lower before the shock when low-downpayment mortgages are chosen more frequently. But this equity effect is compounded by the selection effects associated with broadening access to mortgage markets. Relaxing approval standards allows agents with lower income and assets to enter mortgage markets. These new borrowers are inherently more prone to default. As discussed above, default typically involves a shock other than a pure home value shock. Selection effects compound the equity effect of high-leverage by populating mortgage markets with borrowers that are more likely to face payment difficulties. We show in section 6.2 that new entrants into mortgage markets and households who opt for low-downpayment loans rather than high-downpayment loans when approval standards are relaxed account for much of the increase in default rates following the home-price collapse.

Besides dealing with selection effects, a structural model also makes it possible to discuss the potential role of policy in the crisis. Some have argued that the fact that recourse is highly limited in law or in practice in most US states greatly magnified the impact of the home value correction on default rates. Broadening recourse has opposing effects. On the one hand, the risk of default falls due to harsher punishment for a given set of asset and income characteristics at origination and average recoveries rise, which lowers interest rates at origination. On the other hand, lower payments allow agents with lower income and assets to enter mortgage markets. This effect on the composition of the borrower pool can offset the direct, loan-level effect of recourse on default. We find that repeating the same 3-stage experiment as above in an economy with broad recourse leads to an increase in the foreclosure rate that is 20% below the peak that occurs when all loans are non-recourse. In an environment with full recourse interest rates are lower hence access to mortgage markets is broader in the pre-boom period. Therefore, relaxed approval standards have a significant impact on households' ability to participate in mortgage markets. Furthermore, given the increased cost of default for borrowers, the use of low-downpayment loans falls. Leverage is thus less prevalent at the onset of the crisis, and, as a result, the impact of the home value correction on default rates falls.

There are several structural models which study foreclosures. While none directly address our question, we briefly mention the closest related papers. Campbell and Cocco (2013) study the effect of differences in loan-to-value and loan-to-income on the foreclosure decision in an environment with a rich structure of exogenous shocks but do not consider the implications of household heterogeneity for contract selection. While we also take house price shocks as exogenous, in our model the characteristics of home-buyers at origination varies endogenously by income and wealth which has important implications for contract selection, the pool of risky borrowers, and mortgage pricing.[4] Unlike us, Chatterjee and Eyigungor (2011) endogenize prices in order to study feedback effects of foreclosures on house prices but approximate mortgage terms using contracts with geometrically declining payments for a stochastic maturity. There are also papers which study the impact of recourse policy on foreclosures. Mitman (2012) considers the interaction of recourse and bankruptcy on the decision to default in an environment with one period mortgages and costless refinance. Hatchondo et. al. (2013) use a life-cycle model to simulate the effect of broader recourse on default rates and welfare, but they broaden recourse to include wage garnishment and, as a result, find a larger effect of recourse on default than we do. 1. They also find that recourse and LTV limits reduce the sensitivity of default rates to fluctuations in aggregate house prices.

Section 2 lays out the economic environment. Section 3 describes optimal behavior on the part of all agents and defines a mortgage market equilibrium. Section 4 discusses our

[4]Other papers which address foreclosures include Guler (2008), Arslan et. al. (2013) and Garriga and Schlagenhauf (2009).

parameterization procedure. Section 5 discusses the connection between leverage and default decisions in our model. Section 6 presents the main transition experiment. Section 7 asks whether broader recourse could have mitigated the foreclosure crisis. Section 8 concludes.

2 Environment

2.1 Demographics, Tastes, and Technologies

Time is discrete and infinite. Each period a constant mass of households are born. We normalize this constant mass so that the unique invariant size of the population is one. Households move stochastically through four stages: youth ($\mathcal{Y}$), mid-age ($\mathcal{M}$), old-age ($\mathcal{O}$), and death ($\mathcal{D}$). At the beginning of each period, young households become mid-aged with probability ρ^M, mid-aged households become old with probability ρ^O, and old households die with probability ρ^D and are replaced by young households.[5]

Each period when young or mid-aged, households receive an idiosyncratic shock to their earnings y_t denominated in terms of the unique consumption good. For $\eta \in \{\mathcal{Y}, \mathcal{M}\}$, these income shocks follow a Markov process with finite support $Y^\eta \subset I\!R_+$ and transition matrices P^η. Earnings shocks obey a law of large numbers. Agents begin life at an income level drawn from the unique invariant distribution associated with the young agent's income process. When old, agents earn a fixed, certain amount of income $y^{\mathcal{O}} > 0$. Where convenient, we will write $Y \equiv Y^{\mathcal{Y}} \cup Y^{\mathcal{M}} \cup \{y^O\}$ for the set of all possible income values.

Households can save $a_t \geq 0$ at any date t and earn the risk-free storage return r with certainty on these savings. For old agents, returns are annuitized so that surviving households earn return $\frac{1+r}{1-\rho^D} - 1$ on their deposits while households who die do so with no wealth.

Households value consumption and housing services. They can obtain housing services

[5] Our model builds on the growing literature on housing choices in dynamic models. See, for instance, Stein (1995), Ortalo-Magné and Rady (2006), Rios-Rull and Sanchez-Marcos (2008), Chambers et. al. (2009), Fisher and Gervais (2010), Kiyotaki et. al. (2010), Favilukis et. al. (2011), Fernandez-Villaverde and Krueger (2011), Landvoigt et. al. (2012) and Karmani (2014).

from the rental market or from the owner-occupied market. On the first market, they can rent quantity $h^1 > 0$. When they become mid-aged, agents can choose to purchase quantity $h_t \in \{h^2, h^3\} \in \mathbb{R}^2_+$ of housing capital. We refer to this asset as a house. While mid-aged, a household which is currently renting receives an exogenous opportunity to purchase a house with probability $\gamma \in [0, 1]$.

Our economy is subject to aggregate uncertainty at date t denoted $s_t \in S \equiv \{L, N, H\}$. We take the unit price q_{s_t} of homes as the exogenous realization of a Markov process defined on:

$$\mathcal{Q} \equiv \{q_L, q_N, q_H\} \in \mathbb{R}^3_+$$

where $q_L < q_N < q_H$ with transition matrix P^q.[6] Rental rates respond to the same aggregate uncertainty so we assume three distinct values $\{R_L, R_N, R_H\}$ which we will calibrate to match the pertinent evidence on price-to-rent ratios.

Once agents own a house of size $h_t \in \{h^2, h^3\}$, the market value of the housing capital they own in any given aggregate state s is $q_{s_t}\epsilon_t h_t$ where ϵ_t is an idiosyncratic shock drawn from

$$\mathcal{E} \equiv \{\epsilon_b, 1, \epsilon_g\}$$

which follows a Markov process with transition matrix P^ϵ. The idiosyncratic shock process is independent of aggregate shocks and obeys a law of large numbers. One possible interpretation of these shocks is "neighborhood effects[7]" which change the market value of the house to a potential buyer independent of aggregate housing price changes. We introduce these

[6] In a previous version of this paper, we assumed a linear technology for transforming consumption goods into housing capital in which case under perfect competition aggregate prices were simply given by the inverse of aggregate housing total factor productivity shocks. Under that interpretation and at a give date t, a risk-neutral agent (the intermediary, say) buys existing homes at unit price $q_t\epsilon_t$, instantaneously transform the resulting housing capital into the consumption good at rate $\frac{1}{q_t\epsilon_t}$, or rebundle it to rent or sell to new homebuyers. When it buys an existing home of size h_t at market value $q_{s_t}\epsilon_t h_t$, rebundling either requires an expenditure of $q_{s_t}(1 - \epsilon_t)h_t$ when $\epsilon_t < 1$ to return the home to marketable value or entails a windfall $q_{s_t}(\epsilon_t - 1)h_t$ when $\epsilon_t > 1$.

[7] While we assume that idiosyncratic shocks obey a law of large numbers, we do not assume that these shocks are independent across households so that clusters of agents one could think of as geographical locations may have ex-ante correlated house values.

idiosyncratic shocks so that even when aggregate home prices are stable, some homeowners experience negative equity after house purchases while other homeowners experience positive capital gains on their houses. We will specify the ϵ process to match the relevant evidence on the dispersion of housing capital gains in the United States.

Households thus face aggregate uncertainty and three sources of idiosyncratic uncertainty – aging shocks, income shocks, and house-specific price shocks. For every household of age $t \in \{0, +\infty\}$, histories are elements of

$$\left[S \times \{\mathcal{Y}, \mathcal{M}, \mathcal{O}, \mathcal{D}\} \times Y \times \mathcal{E}\right]^t.$$

Households order history-contingent processes $\{c_t, h_t\}_{t=0}^{+\infty}$ according to the following utility function:

$$E_0 \sum_{t=0}^{\infty} \beta^t u(c_t, h_t)$$

where for all $t \geq 0$, $c_t \geq 0$, $h_t \in \{h^1, h^2, h^3\}$, and

$$u(c_t, h_t) \equiv \log c_t + \log[h_t \times \theta(h_t)]$$

with

$$\theta(h^3) = \theta(h^2) > 1 = \theta(h^1)$$

so that homeowners enjoy a proportional utility premium over renters. We think of θ as capturing any enjoyment agents derive from owning rather than renting their home, but it also serves as a proxy for any pecuniary benefit associated with owning which we do not explicitly model.

For all date t, owners of a house of size $h_t \in \{h^2, h^3\}$ bear maintenance costs $\delta q_{s_t} h_t$ where $\delta > 0$.[8] Owners who turn old must sell their house. Since this is the only source of exogenous

[8]We assume that maintenance costs depend only on the aggregate state of the economy (i.e. q_s) and do not include idiosyncratic shocks (ϵ). Assuming that idiosyncratic shocks also affect maintenance costs does not have a significant impact on our results.

sales in our model one could think of this possibility as capturing events such health shocks or divorce that constrain agents to sell their home and experience a permanent change in their income prospects.

The economy also contains a financial intermediary which we model as an infinitely-lived risk-neutral agent that holds household deposits and can store these savings at net return $r \geq 0$ at all dates.

2.2 Mortgages

Households that purchase a house of size $h_t \in \{h^2, h^3\}$ at time t must finance this purchase with a fixed rate mortgage contract of maturity T with downpayment fraction $\nu_t \in \{LD, HD\}$. Specifically, the mortgage requires a downpayment of size $\nu_t q_{s_t} h_t$ and stipulates an interest rate $r_t^\nu(a_t, y_t, h_t; s_t)$ that depends on the household's wealth and income characteristics at origination, the size of the loan (which obviously depends on house prices q_{s_t} and the size of the house h_t), and state dependent mortgage approval standards parameterized by α_{s_t}. Given this interest rate, constant payments $m_t^\nu(a_t, y_t, h_t; s_t)$ and a principal balance schedule $\{b_{t,n}^\nu(a_t, y_t, h_t; s_t)\}_{n=0}^{T-1}$ can be computed using standard fixed annuity calculations, where $n = 0, 1, ..., T-1$ denotes the period following origination.[9]

A simple way to specify approval standards on mortgages originated at date t is to assume that a household applying for a mortgage must meet a payment-to-income (PTI) requirement. Specifically, in order to qualify for a mortgage with downpayment ν_t at time t, a mid-aged

[9]Suppressing initial characteristics for notational simplicity, then

$$m_t^\nu = \frac{r_t^\nu}{1 - (1 + r_t^\nu)^{-T}} (1 - \nu_t) q_{s_t} h_t$$

and

$$b_{t,n+1}^\nu = b_{t,n}^\nu (1 + r_t^\nu) - m_t^\nu,$$

where $b_{t,0}^\nu = (1 - \nu_t) q_{s_t} h_t$.

household of type (a_t, y_t) who wants a loan of size $(1 - \nu_t)q_{s_t}h_t$ must satisfy

$$\frac{m_t^{\nu}}{y_t} \leq \alpha_{s_t} \tag{2.1}$$

where $\alpha_{s_t} > 0$ for all aggregate states. Even though the PTI requirement is the same across downpayment sizes,[10] a given household is less likely to qualify for a high-leverage loan than a low-leverage loan since they carry a higher interest rate in equilibrium and start with a higher balance.

Varying α will enable us to generate fractions of high leverage originations that mimic Figure 1 and trace the consequences of this change. While we do not view this specific aspect of our model as a deep theory for why the frequency of high leverage loans started increasing in the late 1990s, the data suggest that PTIs did rise during the housing boom. As evidence for this, take the Single-Family Loan-Level Dataset which contain information on Debt-to-Income ratios – the ratio of *all* debt payments to income, including credit card payments and the like – at origination for fully-amortizing 30-year fixed-rate single-family mortgages Freddie Mac acquired between 1999 to 2011. DTI ratios exceed PTI ratios since they include non-mortgage debt payments but DTIs and PTIs are highly correlated. In those data, DTIs rose from about 32% in 1999 to 37.5% in 2006 and returned to near their 1999 level by 2011.[11] Furthermore, as we discuss in detail in section 4.3, Survey of Consumer Finance data suggest that loan-to-income ratios rose noticeably on purchase loans during the housing boom. While our model generates such an increase for several reasons – including the fact that the relaxation of approval standards allows lower income households to obtain a mortgage – this significant increase in loan-to-income ratios is consistent with a change in

[10] FHA loans, which account for most high leverage loans in Figure 1 prior to 1998, had formal PTI limits in the 1990s that were only slightly lower than those typical of conventional loans (see Bunce et. al., 1995, for a discussion).

[11] Bokhari et. al. (2013) report similar results for single-family home loans purchased by Fannie Mae. Similarly, according to data released by the FHFA in 2011 (see Mortgage Market Note 11-02, available at http://www.fhfa.gov/webfiles/20686/QRM_FINAL_ALL.pdf), the fraction of first-lien, single family mortgages acquired by government sponsored enterprises with a PTI above 28% or a total monthly debt-to-income (or "back-end DTI") ratio above 36% doubled from 38% in 1998 to 77% in 2007.

PTI requirements.

The set of mortgage terms from which a given household can choose is endogenous and must be consistent in equilibrium with certain conditions. Specifically, let $K_t(a_t, y_t, h_t; s_t) \subset \{LD, HD\}$ be the set of feasible downpayment options on a mortgage offered to a household with characteristics (a_t, y_t) which wants to purchase a house of size h_t at price q_{s_t} under approval standards α_{s_t}. The set K_t must satisfy the following conditions in equilibrium: (i) the downpayment must budget feasible given household wealth; (ii) the payment-to-income requirement is satisfied; and (iii) the lender must expect to make zero profits on such mortgages (these conditions will be made rigorous below). Of course, in equilibrium, the set K_t may be empty.

Households can terminate a mortgage contract written at date t after n periods in one of two ways. First, they can sell the house at the start of the period which yields $q_{s_{t+n}} \epsilon_{t+n} h_t - b^{\nu}_{t,n}$ after repaying the outstanding balance on their loan. Second, they can default on the payment they owe. In that case they are evicted at the end of the period and the house becomes the intermediary's property.[12] When default happens at date $t+n$ the value of recoveries is

$$(1-\chi) q_{s_{t+n}} \epsilon_{t+n} h_t$$

in consumption terms where $q_{s_{t+n}} \epsilon_{t+n} h_t$ is the house value at the start of date $t+n$ while $\chi > 0$ captures the value lost to legal costs, lack of maintenance, foreclosure delays and the like. The intermediary collects

$$\min\{(1-\chi) q_{s_{t+n}} \epsilon_{t+n} h_t, b^{\nu}_{t,n}\}$$

[12] According to Loan Processing Services' *Mortgage Monitor* report (available at http://www.lpsvcs.com), loans in foreclosure in January 2008 had been delinquent for an average of 255 days. That same average is 956 days in the February 2014 report. This number does not include any remaining time to foreclosure completion for loans in those respective samples or the average length of post-foreclosure eviction delays.

while defaulting household receive

$$\max\{(1-\chi)q_{s_{t+n}}\epsilon_{t+n}h_t - b^{\nu}_{t,n}, 0\}$$

at the start of the period.[13]

Homeowners who become old at the start of a given period must sell. We classify this type of termination as a default when it happens with negative equity, i.e. $q_{s_{t+n}}\epsilon_{t+n}h_t - b^{\nu}_{t,n} < 0$. Mid-aged homeowners are always better off defaulting than selling when their equity is negative. All negative equity transactions, therefore, are foreclosures in our model. On the other hand, because homeowners who default get to stay in their home for one period rent-free and maintenance-free, some households may choose to default with positive equity. Clearly however and as we will discuss in the quantitative section, only households with comparatively little home equity will find this optimal.

2.3 Timing

The timing in each period is as follows. At the beginning of the period, agents discover whether or not they have aged and receive a perfectly informative signal about their income draw. Aggregate and idiosyncratic house price shocks are also realized at the beginning of the period. Owners then decide whether to sell their home. Renters discover whether or not home-buying is an option at the beginning of the period. Agents who just turned mid-aged get this option with probability one. Agents who get the home-buying option make their housing and mortgage choice decisions at the beginning of the period, after all uncertainty for the period is resolved. Downpayments are thus made at the beginning of the period. At the end of the period, agents receive their income, mortgage payments are made or default happens, and consumption takes place.

[13] Measuring the present value of recoveries at the start of the period rather than at the end simplifies the statement of the households' and the intermediary's problems. For more discussion of transaction costs associated with the foreclosure process, see Hayre and Saraf (2008).

3 Optimal Household and Intermediary Policies

This section provides recursive formulations of the problems solved by households and the intermediary and defines a mortgage market equilibrium. While we take home prices and rental rates as given, mortgages rates must be optimal from the point of view of the intermediary given how households make termination decisions. To ease notation, we drop all time markers using the convention that, for a given variable x, $x_t \equiv x$ and $x_{t+1} \equiv x'$.

3.1 Households' Problem

3.1.1 Old Agents

In aggregate state s, the individual state of old households is fully described by their asset position $a \geq 0$. The value function for an old agent with assets $a \in \mathbb{R}_+$ solves

$$V_O(a; s) = \max_{a' \geq 0} \left\{ u\left(c, h^1\right) + \beta(1 - \rho^D) E_{s'|s} V_O(a'; s') \right\}$$

s.t.

$$c = a\frac{(1 + r)}{1 - \rho^D} + y^O - h^1 R_s - a' \geq 0.$$

Note that even though old agents do not own homes, the aggregate value of the housing good affects their welfare because it moves the rental rate.

3.1.2 Mid-aged Agents

For mid-aged agents we need to consider three distinct cases depending on housing status.

Case 1: Renter

If the mid-aged household enters the period as a renter (R), the value function is:

$$
\begin{aligned}
V_M^R(a, y; s) &= \max_{c' \geq 0, a' \geq 0} u(c, h^1) + \beta\rho^O E_{s'|s}\left[V_O(a'; s')\right] \\
&\quad + \beta(1-\rho^O) E_{y',s'|y,s} \left[\begin{array}{c} (1-\gamma) V_M^R(a', y'; s') \\ + \gamma V_M(a', y', n=0; s') \end{array} \right]
\end{aligned}
$$

s.t.

$$c + a' = y + a(1+r) - R_s h^1$$

where $V_M(a', y', n = 0; s')$, defined below, is the value function for mid-aged agents who have the option to buy a home given their assets and income and given the aggregate state.

Case 2: Existing Homeowners

Households who already own a home have to decide whether to remain homeowners or to become renters by selling or defaulting. As in the case of renters, their value function depends on their asset, their income and aggregate conditions, but it also depends on the current market value of their home (hence on ϵ), on the age n of their loan, and on the choices they made when their mortgage was originated. Let (ν, κ) be the tuple of mortgage characteristics at origination where $\kappa = (\widehat{a}, \widehat{y}, \widehat{h}; \widehat{s})$ denotes the origination state. This original information pins down mortgage payments $m^\nu(\kappa)$ and the remaining balance $b_n^\nu(\kappa)$ under the existing contract. Equipped with this notation, we can define three value functions for homeowners. For households who choose to sell their home, the value function is:

$$
\begin{aligned}
V_S^{(\nu,\kappa)}(a, y, \epsilon, n; s) &= \max_{c \geq 0, a' \geq 0} u\left(c, h^1\right) + \beta\rho^O E_{s'|s} V_O(a'; s') + \beta(1-\rho^O) E_{s',y'|s,y} V_M^R(a', y'; s') \\
s.t.\ c + a' &= y + a(1+r) - R_s h^1 + (q_s \epsilon \widehat{h} - b_n^\nu)(1+r).
\end{aligned}
$$

Sellers become renters immediately but collect any positive equity they have in their home.

For homeowners who choose to default, the value function is:

$$\begin{aligned}
V_D^{(\nu,\kappa)}(a,y,\epsilon,n;s) &= \max_{c\geq 0, a'\geq 0} u\left(c,\widehat{h}\right) + \beta\rho^O E_{s'|s} V_O(a';s') + \beta(1-\rho^O) E_{s',y'|s,y} V_M^R(a',y';s') \\
s.t.\ c + a' &= y + a(1+r) + \max\{(1-\chi)q_s\epsilon\widehat{h} - b_n^\nu, 0\}(1+r).
\end{aligned}$$

Indeed, defaulting households enjoy the home-ownership premium for one period before being evicted and do not need to make their mortgage payment or pay for maintenance. If recovery proceeds net of foreclosure costs exceed the loan balance, they receive the difference. Finally, for households who choose to remain in their home and keep current on their mortgage the value function is:

$$\begin{aligned}
V_H^{(\nu,\kappa)}(a,y,\epsilon,n;s) &= \max_{c\geq 0, a'\geq 0} u\left(c,\widehat{h}\right) + \beta\rho^O E_{\epsilon',s'|\epsilon,s}\left[V_O(a' + \max\{q_{s'}\epsilon'\widehat{h} - b_{n+1}^\nu(\kappa), 0\}; s')\right] \\
&\quad + \beta(1-\rho^O) E_{y',\epsilon',s'|y,\epsilon,s}\left[V_M^{(\nu,\kappa)}(a',y',\epsilon',n+1;s')\right] \\
s.t.\ c + a' &= y + a(1+r) - m^\nu(\kappa) 1_{\{n<T\}} - \delta q_s h.
\end{aligned}$$

Overall then for middle-age homeowners,

$$V_M^{(\nu,\kappa)}(a,y,\epsilon,n;s) = \max\left\{V_S^{(\nu,\kappa)}(a,y,\epsilon,n;s), V_D^{(\nu,\kappa)}(a,y,\epsilon,n;s), V_H^{(\nu,\kappa)}(a,y,\epsilon,n;s)\right\}$$

We will write $S^{(\nu,\kappa)}(a,y,\epsilon,n;s) = 1$ when the selling option dominates while $D^{(\nu,\kappa)}(a,y,\epsilon,n;s) = 1$ when defaulting is optimal. Both policy choices are set to zero otherwise.

Case 3: The Option to Buy a House

A renter who receives the option to buy a home at the start of a given period must decide whether to exercise that option and, if they become homeowners, what mortgage to use to finance their house purchase. Let $K(\kappa) \subset \{LD, HD\}$ be the set of feasible downpayment options on a mortgage offered to a household given contract-relevant characteristics $\kappa = (a,y,h;s)$ at origination.

The household's value function solves:

$$
\begin{aligned}
V_M(a,y,n=0;s) \;&=\; \max_{c\geq 0, a'\geq 0, h\in\{h^1,h^2,h^3\}, \nu\in K} u(c,h) + \beta\rho^O E_{\epsilon',s'|1,s}\left[V_O(a'+\max\{q_{s'}\epsilon' h - b_1^\nu(\kappa),0\};s')\right] \\
&\quad + \beta(1-\rho^O)E_{y',\epsilon',s'|y,1,s}\left[\begin{array}{c} 1_{\{h=h^1\}}\left(\begin{array}{c}(1-\gamma)V_M^R(a',y';s') \\ +\gamma V_M(a',y',n=0;s')\end{array}\right) \\ +1_{\{h\in\{h^2,h^3\}\}}\left(V_M^{(\nu,\kappa)}(a',y',\epsilon',n=1;s')\right)\end{array}\right]
\end{aligned}
$$

where if $h=h^1$, then

$$c + a' = y + a(1+r) - R_s h^1$$

and if $h \in \{h^2, h^3\}$, then the following conditions must hold

$$
\begin{aligned}
c + a' \;&=\; y + (1+r)\left[a - \nu q_s h\right] - m^\nu(\kappa) - \delta q_s h \\
a \;&\geq\; \nu q_s h \qquad (3.1) \\
\frac{m^\nu(\kappa)}{y} \;&\leq\; \alpha_s. \qquad (3.2)
\end{aligned}
$$

3.1.3 Young Agents

The value function of a young household depends only on their assets and income and on aggregate conditions. It solves:

$$V_Y(a,y;s) \;=\; \max_{c\geq 0, a'\geq 0} u(c,h^1) + \beta E_{y',s'|y,s}\left[(1-\rho^M)V_Y(a',y';s') + \rho^M V_M(a',y',n=0;s')\right]$$

s.t.

$$c + a' = y + a(1+r) - R_s h^1.$$

3.2 Intermediary's Problem

All possible uses of deposits must earn the same return for the intermediary. This implies that the expected return on originated mortgages net of expected foreclosure costs must cover the opportunity cost of funds. The intermediary incurs mortgage service costs which we model as a premium $\phi > 0$ on the opportunity cost of funds loaned to the agent for housing purposes.

The expected present value of the contract to the intermediary depends on the likelihood that the borrower will sell or default in the future. When the borrower gets old, the house is sold with probability one. When this occurs with negative equity, the intermediary incurs transaction costs. Consider then a borrower who becomes old with origination characteristics (ν, κ), a mortgage of age n, idiosyncratic value shock ϵ and under aggregate state s. The present value of recoveries for the intermediary in that case is given by:

$$W_O^{(\nu,\kappa)}(n, \epsilon; s) = \min\{[1 - 1_{\{q_s \epsilon \widehat{h} < b_n^\nu(\kappa)\}} \chi])q_s \epsilon \widehat{h}, b_n^\nu(\kappa)\}.$$

The indicator function reflects the fact that transaction costs are borne by the intermediary in that event if and only if equity is negative.

We can now define the expected present value to the intermediary of an existing mortgage contract with origination characteristics (ν, κ) held by a mid-aged home-owner with current characteristics (a, y, ϵ, n) and given the aggregate state s by $W_n^{(\nu,\kappa)}(a, y, \epsilon; s)$. If the mortgage is paid off $(n \geq T)$ then $W_n^{(\nu,\kappa)} = 0$. Otherwise,

$$\begin{aligned} W_n^{(\nu,\kappa)}(a, y, \epsilon; s) = & \ (S^{(\nu,\kappa)} + D^{(\nu,\kappa)})(a, y, \epsilon, n; s) \min\{(1 - D^{(\nu,\kappa)}(a, y, \epsilon, n; s)\chi) q_s \epsilon \widehat{h}, b_n^\nu(\kappa)\} + \\ & \frac{[1 - (S^{(\nu,\kappa)} + D^{(\nu,\kappa)})(a, y, \epsilon, n; s)]}{1 + r + \phi} \times \left(m^\nu(\kappa) + E_{y',\epsilon',s'|y,\epsilon,s} \left[\begin{array}{c} (1 - \rho^O) W_{n+1}^{(\nu,\kappa)}(a', y', \epsilon'; s') \\ + \rho^O W_O^{(\nu,\kappa)}(n+1, \epsilon'; s') \end{array} \right] \right) \end{aligned}$$

Indeed, in the event of a termination (i.e. $S^{(\nu,\kappa)} + D^{(\nu,\kappa)} = 1$), the bank either recovers the loan's balance or, if lower and in the event of default, foreclosure proceeds. If the homeowner stays in her home (i.e. $S^{(\nu,\kappa)} + D^{(\nu,\kappa)} = 0$), the bank receives the mortgage payment and the mortgage ages by one period.

If the household was a renter and receives an exogenous opportunity to purchase a house in state $(\widehat{a}, \widehat{y}; \widehat{s})$, the household qualifies for a mortgage with downpayment ν on a house of size $\widehat{h} \in \{h^2, h^3\}$ only provided it can make the associated downpayment (i.e. constraint (3.1) is satisfied) and it meets the PTI requirement (i.e. constraint (3.2)) If either (3.1) or (3.2) is violated at origination, we set $W_0^{(\nu,\kappa)} = 0$. Otherwise:

$$W_0^{(\nu,\kappa)}(\widehat{a}, \widehat{y}, \epsilon = 1; \widehat{s}) = \frac{m^\nu(\kappa)}{1+r+\phi} + E_{y',\epsilon',s'|y,1,s} \left[\begin{array}{c} (1-\rho^O)\frac{W_1^{(\nu,\kappa)}(a',y',\epsilon';s')}{1+r+\phi} \\ +\rho^O \frac{W_O^{(\nu,\kappa)}(1,\epsilon';s')}{1+r+\phi} \end{array} \right].$$

Given the interest rate schedule $r^\nu(\kappa)$ which implies $m^\nu(\kappa)$, the intermediary expects to earn zero profit on a loan contract with characteristics κ if

$$W_0^{(\nu,\kappa)}(\widehat{a}, \widehat{y}, 1; \widehat{s}) - (1-\nu)\widehat{q}_s \widehat{h} = 0. \tag{3.3}$$

Assuming free-entry into intermediation activities, it must be in equilibrium that the set $K(\kappa)$ of mortgage contracts and interest rate schedules $r^\nu(\kappa)$ available for the purchase of a home of size $\widehat{h} \in \{h^2, h^3\}$ for a household with characteristics $(\widehat{a}, \widehat{y})$ in aggregate state s satisfy condition (3.3) along with (3.1)-(3.2).[14]

3.3 Mortgage Market Equilibrium

A mortgage market equilibrium is a fixed point of the following mapping. Given a menu of mortgages, we obtain optimal policy functions for all households. In turn, given household policy functions, the menu of mortgages must solve the intermediary's problem for each possible set of characteristics at origination. Appendix A describes how we find the associated fixed point.

Furthermore, from any given set of initial conditions and given any realization of aggregate

[14] As discussed at length by Quintin (2012), there may be several interest rate offerings that produce zero expected profits, even at equal downpayment, since the endogeneity of default generically makes W_0 discontinuous and non-monotonic. Computationally, we need to make sure that among rates that satisfy the zero-profit constraint for a given set of origination characteristics, the most favorable to the household prevails, which prevents us from using geometrically convergent search methods such as bisection. Instead, we start the search for the best possible rate from $r + \phi$ and crawl forward until condition (3.3) is met. This is the most time-consuming part of the algorithm we describe in appendix A.

shocks, our model implies a sequence of distributions of households across asset levels, income, age, and housing choices. Equations B.1 to B.4 in Appendix B define the mapping from aggregate price shocks to distributions. Of particular interest in some of our quantitative experiments in sections 4 and 5 are the distributions of household states that follow infinite draws of constant aggregate shocks. Specifically, we will think of the pre-boom period (1991-98) as following a long period of normal aggregate shocks, $\{q_t = q_N\}_{t=0}^{+\infty}$, and refer to the model moments calculated at this distribution as the "pre-98 benchmark." Similarly, we will refer to model moments obtained from the distribution that would follow an infinite draw of high home values and relaxed approval standards as "long boom" moments.

The quantitative experiments we perform below are partial equilibrium exercises since we take home values and rental rates as exogenously given. In an earlier version of this paper (see section 3.2 of Corbae and Quintin, 2010), we endowed the intermediary with a linear transformation technology between the housing good and the consumption good. In that case, the relative price of housing is pinned down in equilibrium by housing total factor productivity in each period while rental rates are determined by an arbitrage condition. Furthermore, appendix D in Corbae and Quintin (2010) states the corresponding housing market clearing condition.

All mortgage loans are priced in such a way that the intermediary is indifferent between storage and funding mortgages and is therefore willing to transform any fraction of its deposits into mortgages so that the mortgage market clears trivially. In all the simulations we present in this paper, aggregate household assets vastly exceed the balance on outstanding mortgages and hence storage investments are strictly positive in all periods. For instance, the total balance of outstanding mortgages represent around 12% of aggregate deposits in the pre-98 benchmark and around 16% of deposits at the end of the housing boom. In that sense, our economy is effectively closed. While the intermediary makes zero profits on its mortgage activities in the long run, it can experience temporary profits and losses due to aggregate shocks.[15] In all our simulations, these profits and losses are negligibly small. Rebating these

[15]For a definition of net profits from mortgage activity at date t, see appendix B in Corbae and Quintin,

profits and losses lump-sum to households, therefore, would have little impact on our results.

4 Parameter Selection

Our main quantitative goal is to simulate a course of aggregate home price shocks that is consistent with the pattern displayed in Figure 3 under various scenarios for approval standards. To that end, we first need to parameterize the model. We take a model period to be 2 years so that we only need to keep track of 15 periods when considering 30-year mortgages.

4.1 Parameters Selected Independently

As evident in Figure 3, real home values were relatively stable between 1890 and 2013 with two exceptions: a span of roughly two decades of low relative home values that begins around 1920, and the recent boom period between 1999 and 2006. In order to approximate these data with our three-point process, we will treat the 1890-1919 and 1940-1998 time span as periods where real home values are at their intermediate, "normal" level q_N, while home values are at their low level q_L between 1920 and 1939 and at their high level q_H between 1999 and 2006. With this convention average home values during low times are about 30% below the corresponding average during normal times and, likewise, the normal-time average is about 30% below the high-time average. In other words, drops from q_H to q_N are of roughly the same relative magnitude as drops from q_N to q_L. To approximate this, we specify

$$\mathcal{Q} = q_N \times (0.7, 1, 1.45).$$

2010. Following the aggregate price collapse in our transition experiment in section 6, the intermediary experiences losses for several periods on mortgages priced before the realization of the aggregate shock. Those losses amount to a small fraction (at most under half of one percent) of aggregate household earnings. Since the losses are so small, to simplify the analysis, we assume that the risk neutral, deep pocket investors in the intermediary bear the ex-post loss.

The normal level q_N of home values will be selected below when we target pre-housing boom moments.[16]

We then specify the transition matrix P^q so that: 1) two deviations from normal value levels are expected in any given century; 2) deviations to q_L are expected to last 20 years (so the probability of transiting L to M is 0.10); and 3) deviations to q_H are expected to last 8 years (so the probability of transiting H to M is 0.25).[17] Since we think of a model period as lasting two years, the transition matrix for the aggregate shock for all t is:

$$P^q = \begin{bmatrix} 0.90 & 0.10 & 0 \\ 0.02 & 0.96 & 0.02 \\ 0 & 0.25 & 0.75 \end{bmatrix}.$$

As for rental rates, Davis et. al (2008) calculate that the ratio of yearly gross rents to house prices is around 5% for much of the 1960-2008 time period with the exception of the boom period when the ratio falls to about 3.5%. Correspondingly, and given our two-year convention, we set $R_N = 0.10 \times q_N$ and $R_H = 0.07 \times q_H$. Since rent-to-price data do not exist to our knowledge for earlier periods, we simply assume that the ratio is also around its typical 10% during period of low prices hence set $R_L = 0.1 \times q_L$.

Next we set demographic parameters to $(\rho^M, \rho^O, \rho^D) = (\frac{1}{7}, \frac{1}{12}, \frac{1}{10})$. Assuming the first period of our agents' life corresponds to age 21 to 22, they get the option to become homeowners on average between ages 35 and 36. By the same token, setting $\rho^O = \frac{1}{12}$ implies that they turn old on average between ages 59 and 60. Finally, $\rho^D = \frac{1}{10}$ implies that agents' final stage lasts 20 years on average.

[16]Real home values peak at near 85% above their previous trough in 2006 but since we are approximating the entire 1999-2006 period with one q level, we are effectively calibrating q_H to its mid-point value during the boom. Another virtue of this parameterization is that it implies a 30% decline in values in the first two years of the crisis which roughly matches the decline in the real US Case-Shiller index between the last quarter of 2006 and the last quarter of 2008.

[17]Obviously, calibrating the expected length of the high-price event to match the exact duration of its unique data counterpart is but one of many ways to pin down expectations but it seems to be the natural starting point. Furthermore, our results are not sensitive to that assumption: calibrating P^q so that the boom is expected to last 20 years rather than 8 years barely changes our main quantitative findings.

Becoming old in our environment constrains agents to sell their home. In our model therefore, ρ^O has a direct impact on the median duration of home-ownership. Setting $\rho^O = \frac{1}{12}$ implies that median duration of home ownership to be around 7 model periods (=14 years) in our benchmark simulations. Based on American Community Survey data, Emrath (2009) estimates that median duration to range from 12 to 15 years for single family home buyers in the US between 1990 and 2007. Thus, we calibrate this shock which forces households to move out of their house to match the median duration of home-ownership in US data.[18]

The income process is calibrated using the Panel Study of Income Dynamics (PSID) survey. We consider households in each PSID sample whose head is between 20 and 34 years of age to be young while households whose head is 35 or older but younger than 60 years old are mid-aged and households whose head is aged 60 years or more are treated as old. Each demographic group in the 1997 and 1999 PSID surveys is then split into income quartiles, where income is the sum of labor income and social security payments for household heads and their spouse. The support for the income distribution is the average income in each quartile in the two surveys, normalized by the median income value for the mid-aged group. This yields a support for the income distribution of young agents of:

$$Y^{\mathcal{Y}} = \{0.1478, 0.5510, 0.8807, 1.7449\},$$

while the support for mid-aged agents is

$$Y^{\mathcal{M}} = \{0.2097, 0.7429, 1.3152, 2.7619\}.$$

Recalling that for simplicity we assume in the model that income for old households is deter-

[18]Since the duration of the mortgage contract is 15 model periods, the moving shock can only lead to a foreclosure if it happens in the first 12 periods of mid-age even in the worst case scenario of a downward aggregate price shock combined with a downward idiosyncratic price shock. Indeed, by that time, agents have paid off over two thirds of their loan. Therefore, assuming agents become mid-aged around 35 years of age, a moving shock cannot lead to a foreclosure for agents older than 59 years old since they have paid off most of their loan. In other words, the shock which causes homeowners to move out of their house leads to a foreclosure only when it happens early in the household's life.

ministic, the same procedure yields $y^O = 0.505$. For those older households of course, social security payments account for the bulk of income. For younger households, social security payments are small and mostly consist of disability support.

We then equate the income transition matrix for each age group to the frequency distribution of transitions across quartiles for households which appear in both the 1997 and 1999 survey. The resulting transition matrix for young agents is:

$$P^{\mathcal{Y}} = \begin{bmatrix} 58.23 & 28.48 & 10.13 & 3.16 \\ 13.56 & 47.80 & 28.81 & 9.83 \\ 5.14 & 18.49 & 48.29 & 28.08 \\ 3.21 & 8.57 & 12.50 & 75.71 \end{bmatrix},$$

while, for mid-aged agents, it is:

$$P^{\mathcal{M}} = \begin{bmatrix} 72.36 & 21.73 & 4.15 & 1.76 \\ 17.95 & 60.99 & 18.34 & 2.73 \\ 5.18 & 16.99 & 63.49 & 14.34 \\ 1.83 & 3.08 & 15.75 & 79.34 \end{bmatrix}.$$

We next let the (two-year) risk-free rate be $r = 0.08$ and choose the maintenance cost (δ) to be 5% in order to match the yearly gross rate of depreciation of housing capital, which is 2.5% annually according to Harding et al. (2007).

The down-payment ratio ν^{HD} is 20% while the maturity T is 15 periods (=30 years). Low-downpayment contracts have the same 30-year term but require no downpayment (i.e. $\nu^{LD} = 0$). The PTI requirement is assumed to be the same for both mortgages and the same whether $q = q_L$ or $q = q_N$. During the boom (when $q = q_H$), PTI constraints are fully relaxed. We will think of the second stage of our transition experiment as a period of high prices and relaxed approval standards, and compare the model's prediction for that stage to the relevant data from the 1999-2006 period. The PTI level when $q \in \{q_L, q_N\}$ will be selected in the joint part of the parameterization, to which we now turn.

4.2 Parameters Selected Jointly

Our strategy to jointly select remaining parameters is to think of the few years that preceded the housing boom (1991-98, that is) as following a long period of normal aggregate shocks. We compute all benchmark moments at the long-run distribution that would obtain following a infinitely long draw $\{q_t = q_N\}_{t=0}^{+\infty}$ of normal aggregate home values.[19] In what follows, we refer to the model moments calculated at this distribution as the pre-98 benchmark. In the next section, we will also refer to the distribution that would follow an infinitely long draw $\{q_t = q_H\}_{t=0}^{+\infty}$ of high aggregate home values and refer to the corresponding moments as long-boom moments.

Like Campbell and Cocco (2012) we make the strong assumption that buying a home is a one-time-only option for computational tractability (i.e. $\gamma = 0$). Forcing agents who have sold their home or defaulted to become renters for the rest of their life enables us to price mortgage contracts for each possible asset-income-house size position at origination independently from rates offered to borrowers with different characteristics. If agents had the option to take another mortgage after they terminate their first contracts, their decisions to default – hence the intermediary's expected profits – would depend on future contracts, which would mean we need to jointly solve a high-dimensional set of fixed points. We emphasize, however, that this does not imply that all home-buyers are identical. Since agents become mid-aged stochastically, the model generates an endogenous distribution of asset-holdings among potential home-buyers. As we will argue in the next section, this heterogeneity in the pool of borrowers matters critically for contract selection.[20]

[19] Alternatively and given the data shown in Figure 3, one could compute model counterparts for pre-1998 moments by starting at the US economy at this long run distribution in 1919, assuming that 10 model periods (20 years) of low prices followed, and that 30 periods (60 years) of normal home price levels followed that low price phase. Predicted model moments are virtually unchanged under that alternative strategy.

[20] While solving for the full mortgage market equilibrium when $\gamma > 0$ drastically increases the computational complexity of the problem, it turns out that the equilibrium mortgage price schedule that obtains when $\gamma = 0$ continues to deliver within-tolerance zero profits on most contracts until γ reaches about 0.25 because

Remaining parameters include the owner-occupied premium (θ), the household discount rate (β), the normal level (q_N) of home prices, the mortgage service premium (ϕ), the PTI level $\alpha_N = \alpha_L$, the foreclosure transaction cost (χ), and the housing commodity space (h^1, h^2, h^3). We normalize the location of the housing space by making $h^1 = 1$ since a parallel shift in (h^1, h^2, h^3) together with an offsetting shift in q_N leaves the equilibrium allocation unchanged. As for the idiosyncratic home price shock, we specify

$$\mathcal{E} = \{1 - \tilde{\epsilon}, 1, 1 + \tilde{\epsilon}\}$$

and

$$P^{\epsilon} = \begin{bmatrix} \lambda & 1-\lambda & 0 \\ \lambda & 1-2\lambda & \lambda \\ 0 & 1-\lambda & \lambda \end{bmatrix},$$

which adds two parameters to be calibrated: $(\tilde{\epsilon}, \lambda) \in [0,1] \times [0, \frac{1}{2}]$. Note that this symmetric specification of the idiosyncratic process implies that households expect zero capital gains absent aggregate shocks. It also implies that the standard deviation of idiosyncratic gains over the first two years of home ownership is $\sqrt{2\lambda}\tilde{\epsilon}$. We will use a data counterpart for that moment to discipline the parameterization of P^{ϵ}.

We select the ten remaining parameters via a simulated method of moments so that, at the long-run distribution associated with aggregate state N, our model best approximates pre-1998 US data counterparts for eleven targets. Our first target is the ownership rate among households whose head is between 30 and 55 years old, and use as model counterpart for this statistic the rate of ownership among agents who have been mid-aged for thirteen periods or fewer. According to Census data, the home-ownership rate is roughly 66% for that age range on average between 1990 and 1998.

household policy functions change little until that threshold is reached. At the same time, for γ values in that range, the average number of homes owned in the pre-98 benchmark for households who do choose to become homeowners when they turn mid-aged remains near one. Combined, these facts imply that our parameterization would change little for $\gamma \in [0, 0.25]$.

Our second target is the average ratio of non-housing assets to income among households whose head is between 36 and 60 years old in the 1998 Survey of Consumer Finance (SCF) survey. The yearly value of this ratio is 2.82, which corresponds to a ratio of assets to two-years worth of income of 1.41. The model counterpart for this moment is the average asset-to-income ratio of mid-aged households.[21]

We then set three housing spending share targets meant to identify the parameterization of (h^2, h^3) and q_N. First, according to the evidence available from the Bureau of Economic Analysis' Personal Consumption Expenditure data, the ratio of rents (in imputed terms for owners) to overall expenditures is near 15%. Second, Green and Malpezzi (1993, p11) calculate that renters in the bottom income deciles in the US spend between 40% and 50% of their income on rent. Correspondingly, we target a ratio of rents to income for renters at income level y_1 of 45%. Third, according to the 1998 Consumer Expenditure Survey, expenditures on shelter account for 17.3% of the expenditures of home-owners.[22]

Next, we target an average yield of 14.5% for the high-down-payment mortgage over a two-year period, which corresponds to 7.25% a year. This target implies a 300 basis points spread in bond-equivalent terms between 30-year conventional fixed-rate mortgage rate and 1-year treasury rates which is consistent with data available from the Federal Housing Finance Board for the 1991-98 time period.

Pinto (2010) estimates that among conventional and FHA mortgages, loans with a CLTV in excess of 97% accounted for roughly 4% of home purchase origination between 1990 and 1998. Glaeser et. al. (2010) estimate on the other hand that mortgages with zero equity at origination accounted for "at least 10%" of purchase originations by 1998. We choose to target a pre-boom fraction of LD originations of 7%.

[21] Because agents only have one asset in our model besides a house, we interpret a as net assets. Our measure of net assets does not include housing-related assets or debts, such as home equity or mortgages. Since agents are not allowed to have negative assets in our model, households who have negative non-housing assets are assumed to have zero assets in the calculation.

[22] Our benchmark parameterization implies a ratio of housing to overall assets of around 50% for homeowners in the pre-98 benchmark experiments. In the 1998 SCF, the ratio of the median value of the primary residence to the median value of all asset holding for homeowners is 57%. Furthermore, that ratio rises in our model during our boom experiment, which is also consistent with what SCF data show.

Since mortgage pricing obviously depends on expected losses in the event of default, we include in our set of targets a loss severity rate defined as the present value of all losses on a given foreclosed loan as a fraction of the default date balance. As Hayre and Saraf (2008) explain, these losses are caused both by transaction and time costs associated with the foreclosure process, and by the fact that foreclosed properties tend to sell at a discount relative to other, similar properties. Using a dataset of 90,000 first-lien liquidated loans, they estimate that loss severity rates range from around 35% among recent mortgages to as much as 60% among older loans. Based on these numbers we choose parameters so that in the event of default and on average,

$$\frac{\min\{(1-\chi)qh, b)}{b} = 0.5$$

where b is the outstanding principal at the time of default and qh is the house value. On average then, the intermediary recovers 50% of the outstanding principal on defaulted loans.

While estimates vary across studies (see Pennington-Cross, 2006, for a review), a typical finding is that foreclosed properties sell for a price that is around a quarter lower than that of observably similar properties. We therefore target a market discount on foreclosed properties of 75%. We define this discount to be the average price of foreclosed properties divided by the average price of regular home sales, after conditioning on size at origination.

The average foreclosure discount and the average loss severity rates are related since part of the loss incurred by intermediaries in the event of default stems from the fact that foreclosed properties tend to be devalued properties. However, a loss in market value of 25% alone could not account for an average loss severity rate of 50%. In the data, this discrepancy reflects the transaction costs associated with foreclosure. Our transaction cost parameter χ proxies for these costs and we use it to bridge the gap between the foreclosure discount and the total loss associated with foreclosure.

Our final two targets are intended to inform the parameterization of the idiosyncratic process. First, we use data from the 1998 SCF to estimate a standard deviation of roughly 22% of reported capital gains on homes purchased in 1996 or 1997 by households whose head is between 35 and 59 years old.[23] Second, we target the rate of mortgage terminations caused by default in 1998. To measure that number, we begin with data from the Mortgage Bankers Association (MBA)'s National Delinquency Survey on the fraction of mortgages that enter the foreclosure process in a given quarter. As Jeske et. al. (2013) or Herkenhoff and Ohanian (2012) among others have pointed out, many foreclosures started do not end up leading to termination and eviction as they do in our model. Jeske et. al. (2013) point to a Mortgage Bankers Association report that suggest that around a quarter of foreclosure started end up in liquidation. To get more direct evidence on the eventual outcome of foreclosure starts we obtained a dataset[24] that tracks all foreclosures started in seven Chicago-area counties between 1998 and 2011 from the time the procedure is legally initiated to its end either by auction or non-auction resolutions. In these data, 52.7% of foreclosures started in 1998 end up leading to an auction. Over the entire 1998-2011 period the ratio of auctions to starts is 49.3%. In light of these statistics, we chose to target half the rate of foreclosure starts reported by the MBA in 1998 which gives a two-year target default rate of 1.45 (or roughly 0.18 on the standard quarterly basis.)

4.3 Model Fit

Tables 1 and 2 show the outcome of minimizing the distance between our model's predictions for the pre-98 benchmark and these targets. Our estimate of normal and low state PTI is $\alpha \approx 18\%$ which, at first glance, seems low given that the limit typically used in mortgage underwriting in the 1990s was closer to 30%.[25] However, in practice, the calculation of

[23] In all our SCF computations, we use the exact calculation methods used by the Federal Reserve Board to produce its biennial *Federal Reserve Bulletin* SCF summary. To minimize the effect of outliers, we remove observations with reported 2-year gains in excess of 200% or 2-year losses in excess of 75%. These represent 3% of house capital gains reports in SCF-weighted terms in the 1998 survey.

[24] We purchased the data from Illinois' Record Information Services (RIS). RIS collects and compile these data from case files of county circuit court. See http://www.public-record.com/ for details. The dataset covers the following counties: DeKalb, DuPage, Kane, Kendall, Lake, McHenry and Will, and includes over 180,000 foreclosure start records between 1998 and 2011. The number of yearly starts hovers between 4,000 and 10,000 until 2006 but then increases to reach a peak of nearly 33,000 in 2010.

[25] See Bunce et. al., 1995. Garriga et al. (2013) estimate that "on average over the past 30-40 years, [mortgage payments] were equivalent to 15-22% of the pre-tax income of the 3rd and 4th quintiles of the U.S.

PTIs includes property taxes, insurance and other costs such as home-owner association fees which we do not model. Furthermore, in our environment, the PTI must proxy for all underwriting criteria that governed approval decisions before the boom. Given these considerations, our model PTI does not seem unreasonable. This PTI level implies that the lowest income households – which represent only 15% of potential home-buyers – do not qualify for any mortgage while households at the second income level only qualify for HD loans. The constraint does not bind at the two other income levels.

Overall, the method of moments we employ reaches a set of ten parameters that produces model moments that are very close to the eleven targets we described in the previous section. A few parameters, notably the home-ownership premium, are imprecisely estimated since moments display little local sensitivity to these values.[26] We found however that experimenting with different values of the home-ownership premium has little impact on our quantitative findings, including most importantly on the outcome of the main counterfactual experiment described in section 6.4.1.

The last column of table 2 shows the average value of our targets and the associated standard deviation based on a sequence of 3,000 aggregate shocks drawn from P^q and starting from the pre-98 long run distribution of household states. Because our economy spends most of its time in the normal state, average moments are near their pre-98 benchmark values and show relatively little volatility. The fraction of LD loans in originations displays the highest volatility. This is because – as we will see and as is the main focus of this paper – that fraction almost quadruples during boom times.

wealth distribution, representing the typical homeowner."

[26]The estimator has asymptotic distribution $\sqrt{N}(\hat{\mathbf{b}} - \mathbf{b}) \xrightarrow{d} \mathcal{N}(0, V)$ where $\hat{\mathbf{b}}$ is the estimated vector of parameter vector $\mathbf{b}$, $V = \left(1 + \frac{1}{S}\right)\left[\hat{d}' W \hat{d}\right]^{-1}$ and $\hat{d} = \frac{\Delta \mathrm{E}[g(x_t, \hat{\mathbf{b}})]}{\Delta \hat{\mathbf{b}}}$ is the numerical derivative of moment condition g, the vector of differences between model and data moments. The weighting matrix W is the inverse of the variance-covariance matrix ($\Omega \equiv W^{-1}$) calculated from $S = 100$ repetitions of $N = 7,000$ households. The normal level (q_N) of home prices and the size ($\tilde{\epsilon}$) of the idiosyncratic home-value shock nearly pin down the rent-to-income ratio for low-income renters and the standard deviation of capital gains. In addition, those two moments have near-zero covariance with other moments in our simulations. As a result, q_N and $\tilde{\epsilon}$ are precisely estimated but this also makes Ω nearly singular, which in turn makes other standard errors (especially λ's) smaller. To estimate standard errors conservatively, we dropped these two moments from the variance-covariance matrix.

In our transition experiment, we will show that the model also makes reasonable predictions for key aspects of the post-98 boom period which we did not explicitly target, including the behavior of home-ownership rates and the rise of high-priced loans during the transition. This section considers another set of predictions we didn't explicitly target: how the use of leverage co-varies with borrower characteristics in the cross-section.

Table 3 compares the cross-sectional predictions of our model for the use of leverage to the corresponding evidence from the 1998, 2007, and 2010 Survey of Consumer Finance. The model counterparts for these time periods are the pre-98 benchmark, the last period of the boom in the transition experiment we will describe in detail in section 6, and the first period of the crisis in that same experiment. The table uses two measures of leverage: loan-to-income (LTY) ratios at origination and the fraction of loans with cumulative loan-to-value ratios above 95%. All data moments are computed for homeowners under 65 years old who bought a home in the two years preceding the survey.

Predicted loan-to-income ratios are below their SCF counterparts in 1998 but are near the data in 2007, at the end of the boom period. The same pattern holds for the frequency of high-CLTV loans which is almost as high in the SCF in 1998 as it is in 2007.[27] Given our parameterization strategy (we target a 7% frequency of high-LTV loans in 1998), the model under-predicts the use of high-leverage loans in 1998 but over-predicts it in 2007. As we will discuss in the transition section however, our model's predictions for the overall fraction of high leverage loans at the onset of the crisis accords well with other sources of data.

Loan-to-income ratios are lower in the 2010 survey than in the 2007 survey in all subgroups, most notably among poor and young home-owners. Our model delivers a fall in LTYs as well since approval standards become tighter when the boom end but the model's predicted correction is more pronounced than in the data.

The model correctly predicts that loan-to-income ratios and the use of high-CLTV loans

[27] The fraction of loans with CLTV higher than 95% rises from 13.5% to 15.5%. The data contain a high number of unreasonably high self-reported CLTVs on recent loans which suggests that the SCF is not a reliable source for measuring average CLTVs at origination. Here we use these data to evaluate whether our model makes reasonable predictions for how leverage should covary with observable characteristics.

should fall with income. There seems to be little relationship between asset holding or age and LTYs in either the model or the data. The model also correctly predicts that low-downpayment loans should be highly concentrated at the bottom of the asset distribution and among young borrowers.[28] Quantitatively, our model exaggerates the concentration of high-leverage loans among asset-poor agents, which may owe to the fact that we only give agents one ex-housing investment alternative. Introducing other investment options could lead more asset-rich agents to take advantage of high-leverage mortgages.

The third section of the table classifies home-owners by age. In the model, we classify a home buyer to be under 35 years of age if they become mid-aged in 12 periods or fewer. There is no clear relationship between age and LTYs but younger households select high-CLTV loans more frequently both in the model and in the data.

The fourth section of the table shows that, both in the model and the data, LTYs tend to rise with loan size. The model has a more difficult time capturing the relationship between loan size and the frequency of LD loans. While our model does produce LD loans among both small and large loans, the SCF data shows that the use of LD loans should be higher for above median loans. The model only predicts such a pattern during the boom.

In summary then, the model misses on some of the quantitative features of cross-sectional patterns in the SCF which is not surprising given that it only contains so many sources of heterogeneity among households. At the same time, the model correctly picks up the parts of the income, asset and age distributions where leverage should be the most prevalent.

5 Leverage and Default in the Long-run

This section discusses the connection between approval standards, leverage and default rates in our model to pave the way for interpreting the transition experiments we perform in the next section.

[28] Since $\gamma = 0$, our simulations do not make predictions for repeat buyers but, to the extent that these would tend to be older buyers in the model, these repeat buyers would presumably be less likely to select high-leverage loans.

5.1 Contract Selection Patterns

Table 4 displays contract selection and housing decisions in the benchmark and in the boom state conditional on a household's asset and income position at origination. In the benchmark, none of the households at the very bottom of the income distribution are able to become home-owners. During a boom, some of the lowest income households whose assets are sufficiently high for the intermediary to expect to break even are able to enter mortgage markets. But all of them make a 20% down-payment because the interest rate the intermediary would need to impose on those households would be prohibitively high if they started with no equity. Poor homeowners are mostly found in the second income quartile. For those households, the asset threshold above which they become home-owners falls from 2.24 to 0.12 as we go from the benchmark to the boom and low-asset agents use the LD mortgage to become home-owners. Households in the third income quartile who have low assets ($a_0 < 0.34$) now opt for larger homes using an LD-loan while those in the intermediate range ($a_0 \in (0.34, 0.63)$) continue to buy large homes but use LD loans in the boom since the price rise makes the downpayment expensive. At the top of the income distribution, all agents buy large homes but those with low assets now opt more frequently for LD loans.

The set of mortgage contracts actually selected depends both on the decision rules displayed in Table 4 and on the cross-sectional income and asset distribution. Figure 4 shows the endogenous asset and income distribution among households (i.e. $\mu^t_{\mathcal{M},n=0}$ as defined in appendix B) in the pre-98 benchmark and following a long boom. Because the income process is highly persistent, asset and income levels are highly correlated. As a result, low-income but high-asset agents are a rare type of homeowner. Even following a long draw of boom home values, these agents turn out to represent less than 2% of home-owners and all but 22% of households who have the lowest income choose to remain renters.

In summary then, LD loans tend to allow agents with lower assets to start participating in mortgage markets, to take on bigger loans, or to put less money down even when they choose to remain at the same loan size. Because the income process is highly persistent, assets and income tend to be correlated hence the greater frequency of LD loans implies a greater frequency of low income borrowers. Combined with the direct effect of the relaxation of PTI constraints, the composition of the pool of borrowers shifts towards the low income and low asset part of the state space.

5.2 Default

As the next section will illustrate, default rates eventually increase during booms as a result of two complementary factors. First, better access to LD mortgages enable agents at the bottom of the asset and income distribution to select into homeownership. These are high-default risk agents because they are more likely to find themselves unable to meet their mortgage payments at some point over the life of the contract. Second, even at equal asset and income conditions at origination, LD loans are associated with higher default rates because agents are slower to build up home equity.

Figure 5 illustrates the link between loan types and default rates by plotting average hazard rates (the fraction of remaining loans that default at all possible loan ages) in the benchmark equilibrium and following a long boom period based on pseudo-panel of 50,000 loans of each type generated by our model. LD loans have a higher propensity to default at all ages in both equilibria. Nevertheless, the gap is small in the benchmark until at least period 6 of the loan. This is because, as we documented above, pre-boom approval standards are such that low income agents do not qualify for high-leverage loans. As a result, as a group, LD borrowers are not much riskier than their HD counterparts. After 6 periods however, the two plots diverge noticeably. By that time high-leverage borrowers remain in positive equity territory even if their house devalues while a bad idiosyncratic shocks continues to send LD borrowers into negative equity territory. In summary then, high-leverage mortgages are not much riskier than HD loans in the pre-boom economy because selection effects are muted by tight approval standards.

In sharp contrast, hazard rates are completely different for the two types of loans following a long boom period. Agents at the bottom of the asset and income distribution take advantage of weakened approval standards to become home-owners. LD borrowers are at a much higher risk of being unable to meet mortgage payments hence default at a much higher frequency, even early in the loan's life. Since low downpayments become much more frequent during the boom and average default rates on those loans rise noticeably, average defaults rates are bound to eventually rise during boom period, as our transition experiments will confirm.

In appendix C, we illustrate the effects of selection and equity effects on default more formally by estimating a traditional competing hazard model on a pseudo-panel of mortgages generated by our model. As should be expected, estimated hazard rates into default rise with loan-to-income at origination and fall with the asset-to-loan ratio, while income and home equity have a negative impact on both hazards. As we discuss in appendix C, this is qualitatively consistent with the empirical literature that studies the determinants of mortgage default decisions.

5.3 Interest Rates

A distinguishing feature of our model is that mortgage terms depend not only on downpayment choices but also on the initial asset and income position of borrowers as well as the size of the loan. Figure 6 plots the menu of equilibrium interest rate offerings conditional on the house size they opt for and their asset and income position at origination in the aggregate boom state.

Some schedules in Figure 6 are left-truncated because agents whose income and assets are too low do not get a mortgage in equilibrium. The left truncation can be thought of as an endogenous borrowing constraint associated with different borrower characteristics. Some agents become mid-aged with asset and income characteristics such that the intermediary could not break even on a mortgage issued to them, which may occur even when the agents have the means to finance the initial downpayment. Among agents who do receive a mortgage offer, rates fall both with assets and income.

While Figure 6 graphs equilibrium offers, Figure 7 graphs the equilibrium distribution of interest rates chosen by mortgage type in the pre-98 benchmark and following a long boom. As evident from comparing the two distributions, the right tail expands. This has two testable implications for observables: the coefficient of variation of mortgage rates should rise during booms and the fraction of high priced or "subprime" loans should increase as well.

The data support both predictions. First, the coefficient of variation in first-lien interest rates among recent borrowers in the SCF data we used in table 3 increases by 30% (from 13.6% to 17.6%) between the 1998 survey and the 2007 survey, at the height of the boom. The model produces a higher increase (from 1.4% to 24.4%) but first-lien SCF data may understate the change in dispersion during the boom since the use of junior mortgages increases drastically during that period.

Second, as we show in section 6, the model predicts that the share of high-priced loans – defined as contracts with a rate at origination 300 basis points above the best-priced loan–[29] in the stock of outstanding mortgages goes from 0% in 1998 to around 14% at the peak of the boom while in MBA data, the share of subprime loans in the stock of mortgages rises from roughly 2% to around 12% during that same period.

Figure 7 also shows that leverage and "subprime" loan pricing are correlated but distinct notions. In particular, we see that some LD loans are originated at a two-year rate around 16%, which is within 300 basis points of the safest loans. These prime high-leverage (LD) loans account for 18% of all originations in the long boom. Further, some HD loans carry two-year rates in excess of 18% making them high priced. These subprime low-leverage (HD) loans account for 12% of high-priced originations. Of course, most (94%) low-leverage loans are prime.

Another prediction of our model is that rates at originations should be negatively correlated with borrowers' assets and income. Appendix D documents this more formally using a

[29] In empirical work, loans are classified as subprime either because they are reported as such by lenders or, more directly, because they carry a significant interest rate premium over the best-priced ("prime") loans at origination.

pseudo-panel of mortgages generated by our model and discusses some empirical evidence in support of that prediction.

6 The Crisis: Transitional Consequences of Leverage

This section describes an experiment designed to answer the question "How much of the post-2006 rise in foreclosures can be explained by the large number of high-leverage mortgage contracts originated during the housing boom?" No parameters were chosen to match data in this section, so all experiments can also be seen as a test of the model.

6.1 A Boom-Bust Experiment

We will think of the recent history of housing markets in the United States as follows. We assume that in 1998 the US economy is near the long-run distribution that would prevail following a long period of normal home values and normal approval standards. We take the following 8 years (1999-2006) as 4 model periods of boom (that is, 4 periods of high home prices and relaxed approval standards). The economy then returns to the normal state. Data counterparts are averages over two-year periods for each period of the transition. The fifth period of the transition, for instance, corresponds to 2007-08, and we think of it as the first two years of the crisis.

Figure 8 plots the outcome of the experiment.[30] Panel (a) shows that once the boom begins, home-ownership rates start rising towards a peak of over 72% at the onset of the crisis. The model thus overshoots the homeownership rise during the boom period by about 2 percentage points but does predict correctly that despite rising home prices participation

[30] The behavior of the equilibrium variables shown in table 2 but not displayed on the Figure is mostly stable during the transition. One slight exception is that the rent-to-income ratio rises to 50% at the peak of the boom since rents increase during that period. Similarly, housing expenditure shares for homeowners rise somewhat due to the increase in aggregate home prices. This is broadly consistent with the available evidence from the Consumer Expenditure Survey. The fraction spent on shelter by homeowners goes from 17.3% in 1998 as mentioned in the parameterization section to 18.7% in 2006.

in owned housing markets rose markedly during that period, before heading back towards its pre-98 level once the crisis strikes.

The frequency of LD loans jumps to over 25% during the boom, as panel (b) shows. Compared to the numbers produced for conventional loans by Pinto (2010, see Figure 1) the rise in LD originations is too sharp which is not surprising since we relax PTIs fully in one period rather than progressively. Nevertheless, the model's predicted origination rates during the boom are near what they are in the data at the peak of the boom.

In the aftermath of the crisis, the share of FHA-insured loans in purchase originations rose above 25%. Furthermore, roughly two-thirds of FHA loans are issued at LTVs in excess of 95%.[31] This suggests that the share of LD loans in origination has remained elevated since the crisis, as shown in panel (b) of Figure 8. Our experiment does not capture that aspect of the evidence which is not surprising since we do not model post-crisis changes in government policy. It should be clear, however, that the post-crisis strength of LD originations in the data cannot influence our counterfactual accounting as long as it was unexpected during the boom period. Indeed, the foreclosure spike is the result of decisions made by agents who already have a mortgage when home values collapse and of the shocks that hit those incumbent borrowers. These borrowers' choice set and decisions are not impacted by the PTIs that new borrowers face. As long as the sudden boom in FHA activity was mostly unforeseen then, the initial behavior of default rates cannot depend on this aspect of the crisis' aftermath.

As we mentioned in the previous section, relaxing approval standards causes the frequency of high-price loans – defined as contracts with a rate at origination 300 basis points above the best-priced loan – to rise, as displayed in panel (c). By that metric, the experiment thus generates a significant subprime boom, one that resembles estimates of the share of subprime loans in the stock of US mortgages available from the Mortage Bankers Association (MBA).

Panel (d) of the Figure shows the key outcome of this transition experiment for our

[31] See pages 16 and 17 of the 2012 US Department of Housing and Urban Development Annual Report to Congress, p17, available for download at http://portal.hud.gov/hudportal/documents/huddoc?id=F12MMIFundRepCong111612.pdf.

purposes: the path of default rates during the boom and following the collapse of home prices. Even though we did not target this in any way, our predicted default rates almost coincide with the data in the last period of the boom. Because we model home prices starkly using three possible values, the default rate falls at the start of the boom as all loans originated at lower aggregate prices receive an equity injection. The effect of that aggregate injection dissipates over time as pre-existing loans exit the stock of mortgages through sale, foreclosure, or simply being paid off.

Default rates increase by 275% once prices collapse relative to their pre-98 baseline. In the National Delinquency Survey data, default rates peak at roughly 256% above its 1998 level so that our transition experiment captures quite closely the post-crisis spike in default rates, over-predicting it by merely 7%. Again, we emphasize that this was not targeted in our estimation so the fact that the model predicts an increase in default rates of the right magnitude provides an important test.

However, our model-predicted default rates peak early relative to the the data. As the quarterly foreclosure numbers in Figure 2 show, default rates begin briefly retreating in 2008 but they spike again in 2009. The two-year averaged default data correspondingly shows a second peak in the second period (i.e the 2009-10 time period) of the crisis. Since the experiment so far only contains a one-time aggregate shock to home prices, it cannot produce elevated default rates for a full 4 years. A possible explanation for the duration of the crisis is that the housing collapse impacted the distribution of household income. Section 6.4.2 explores this possibility.

6.2 The Importance of Selection

Table 5 shows default rates by borrower types in the pre-1998 benchmark and in the first period of the crisis. In a pure accounting sense, the contribution of LD loans to the increase in foreclosure rates between 1998 and the peak of the crisis is easy to measure. To see this, let ξ_t^ν be the share of loans of type $\nu \in \{HD, LD\}$ in the stock in period t while D_t^ν is the default rate on those loans. Using this notation and as a matter of accounting, the overall default rate at time t is always the sum of two parts

$$D_t = \xi_t^{LD} D_t^{LD} + \xi_t^{HD} D_t^{HD}.$$

One way to measure the contribution of LD loans to the increase in default rates between 1998 and the start of the crisis is to perform a traditional Oaxaca decomposition and divide the increase in the first element of the sum, namely

$$\Delta\left(\xi_t^{LD} D_t^{LD}\right) \approx \Delta\left(\xi_t^{LD}\right) D_t^{LD} + \xi_t^{LD} \Delta\left(D_t^{LD}\right)$$

by the total increase $\Delta(D)$ in the default rate.[32] In this accounting, both changes in the pool of borrowers (i.e. $\Delta\left(\xi_t^{LD}\right)$) and changes in default rates of that pool (i.e. $\Delta\left(D_t^{LD}\right)$) matter. The table shows that both are large, which implies that the accounting contribution of LD loans to the increase in overall default rates is large as well, at about 48%.

This number is difficult to interpret, however, because as this section shows, new entrants and switchers into the LD pool of borrowers account for much of the increase in $\xi_t^{LD} D_t^{LD}$. Restricting leverage would presumably cause many of these borrowers to make different contract choices, exit mortgage markets altogether and/or affect their propensity to default. In particular, whenever $\xi_t^{LD} D_t^{LD}$ changes, $\xi_t^{HD} D_t^{HD}$ is bound to change as well. Most obviously, as different households select into the set of HD borrowers when access to leverage changes, D_t^{HD} is likely to be affected. Our model enables us to measure the effects of access to leverage while taking all endogenous effects into account.

Almost 10% of LD holders in the first period of the crisis are households who took a loan during the boom and, given their asset and income when they were given the option to buy a home, would have rented in the pre-98 benchmark. Table 5 shows that in the first period of the crisis these "new entrants" in the LD sample default at nearly 9 times the

[32]Here Δ is the time difference operator between 2007 and 1998. That is, $\Delta\left(\xi_t^{LD}\right) = \xi_{2007}^{LD} - \xi_{1998}^{LD}$.

pace of "incumbent" LD households (an incumbent household is defined as one which already had taken an LD loan before the boom started or had characteristics such that if given the opportunity to purchase would have opted for an LD loan pre-98). In addition, roughly one third of LD holders at the onset of the crisis are "loan-type switchers." These households took their loan during the boom and, in the pre-98 economy, would have opted for an HD loan by choice or by constraint. These loan-type switchers default at a 40% higher pace than incumbents do when the crisis strikes. Entry also contributes to the increased default rates on HD loans. Roughly 8% of HD holders are new entrants when the crisis strikes and they default at over 6 times the pace HD incumbents do. No household who takes an HD loan during the boom would have taken an LD loan pre-98 (which accounts for "N.A." in the table).

Given these fundamental changes in the composition of each pool of borrowers during the boom, measuring the effect of different mortgage access scenarios on default rates requires predicting how these scenarios change mortgage housing choices. It also requires predicting the default decisions of households who are constrained to change mortgage choices but remain home-owners. Not only do we need to predict who would exit mortgage markets given different access scenarios, we also need to predict how loan-switchers would default if forced to return to their pre-98 choices. The next section uses our model to run counterfactual experiments that take these endogenous effects into account.

The table also shows that, in our model, default rates are not that different across loan types pre-98. As we discussed in the long-run section, the gap in default propensities increases in the boom state. But it is following the aggregate price correction that the two loan types truly separate in terms of their propensity to default. This parting of default rates is broadly consistent with the evidence presented in Figure 4 in Gerardi et. al. (2009.) However, our default rates begin drifting significantly apart starting in period 2 of the boom period (i.e in 2001-2002) which is somewhat earlier than the evidence in Gerardi et. al. (2009) would seem to suggest.

6.3 Default Patterns during the Transition

A growing empirical literature (see, e.g., Gerardi et al., 2009 or Buttha et al., 2010) uses pre- and post-crisis mortgage data to study the importance of various shocks in households' decisions to default. This literature has documented that most defaults involve negative equity, but, at the same time, that most households with negative equity choose not to foreclose. Most foreclosures thus appear to involve a combination of negative equity and other shocks. In this section we will show that our model is consistent with these empirical patterns.

Table 6 breaks down defaults in three subcategories for each mortgage type. Moving shocks refer to homeowners who become old and must sell with negative equity.[33] Defaults by mid-aged homeowners whose income has fallen compared to what it was at origination are classified as being caused by an income shock.[34] The final column of each panel includes all defaults that feature neither a moving nor an income reduction. Almost all the households in the "Neither" column in the table have zero assets when they choose to default. Since negative income shocks lead to lower assets, the table thus understates the importance of income shocks in default decisions. The boom panel corresponds to the 8-year boom period in our transition experiment. The bottom panel of the table shows default shares once the boom period comes to an end and home prices fall back to their normal value (the "bust").

The table shows that most default involves a moving shock or a decline in income. In the benchmark economy, the moving shock accounts for the vast majority (88% overall) of defaults but the share of defaults caused by the moving shock becomes much lower during the boom (one third overall) and the bust (about 55%) as the share of LD loans and the participation of riskier borrowers both rise.

In both the benchmark economy and the boom economy, the vast majority (94% in the

[33]Recall that we calibrate the frequency of this shock (i.e. ρ^O) to match the median duration of homeownership in the U.S.

[34]This definition of income shocks is meant to approximate standard practice in empirical work on the determinants of default where a central question is whether current income or unemployment characteristics of borrowers can account for default decision patterns.

pre-98-benchmark, 73% in the boom, 95% during the bust) of defaults involve negative equity. The reason for this is that agents who have positive equity in their house can always sell unless they can't make their mortgage payment. The households that default with positive equity do so because the benefits of staying in their home rent-free and maintenance-free for two years outweigh the fact that defaulting causes them to lose all or most of their home equity to foreclosure transaction costs. The few households that default with positive equity do so with under one-fifth the average level of equity of sellers.[35] While most foreclosures involve negative home equity, most households (roughly 91% in the pre-98 benchmark, 87% in the Long Boom) with negative home equity choose to keep their home and continue meeting their mortgage obligations.

6.4 Leverage Counterfactual

6.4.1 No change in Approval Standards

To quantify the role of leverage in the crisis using our model, we simulate a scenario with the same price path as in the baseline experiment but make approval standards (PTIs on both types of loans) during the boom the same as during normal times. The simulation assumes that agents fully expect this counterfactual scenario but this has no bearing whatsoever on our results. In turns that the level of PTI agents expect during boom times has barely any influence on the pre-98 steady state. It follows that neither the benchmark transition we show in section 6.1 nor the counterfactual transition we show here depend significantly on assumptions one makes about the extent to which the change in approval standards that characterizes boom periods is anticipated.

Since the boom period features more costly homes without any offsetting changes in access to mortgages under the counterfactual scenario, home-ownership rates fall and the use of high leverage loans remains virtually unchanged compared to the pre-98 period, as Figure 9

[35] The average ratio of equity to value for sellers is 52% in the pre-98 benchmark, 45% during the boom and 50% during the bust.

displays. Default rates actually fall prior to the boom because only the safest (high-income and high-asset) borrowers remain home-owners. Default rates do spike when aggregate home prices collapse but only rise 105% above their pre-boom level in the first two years of the crisis, which is roughly 38% of the baseline increase in default rates. This experiment thus suggests that relaxed approval standards and the resulting greater access to LD loans can account for roughly 62% of the rise in foreclosure rates in the first two years of the crisis.[36]

Our counterfactual experiment makes the strong assumption that the path for home prices would have been the same even under very different mortgage approval standards. These standards, of course, may have directly contributed to the price boom and, eventually to the price collapse. By ignoring this additional channel through which approval standards may have contributed to the crisis in the counterfactual, our already large numbers may actually understate the role changing approval practices played in the foreclosure crisis.[37]

This counterfactual accounting also ignores the effect of the mortgage crisis on aggregate income and the fact that mortgage participation was also affected by declining mortgage rates during the boom. We will now evaluate the sensitivity of our findings to these factors.

6.4.2 Aggregate Income Shock

After declining for two quarters in late 2008, default rates flared up again to reach a new peak in the last quarter of 2010. In our experiment, the only post-2006 shock occurs in the first two years (the first model period) of the crisis when prices fall back to their normal level and default rates begin declining noticeably thereafter. One explanation for the persistence of high default rates in the data is the fact that the housing crisis was followed by a deterioration of household income. To simulate the potential role of this second shock while retaining tractability, we consider the effect of a one-time, fully unexpected shock to the income distribution at the start

[36] Gerardi et al. (2009) run a related counterfactual using an econometric approach and find that changes in mortgage practices account for about half of the foreclosure crisis. Section E of the appendix discusses the relationship between our approach and theirs in more details.

[37] To see this, assume that all of the change in prices was caused by a change in approval standards. Then no change in standards implies no change in price and no change in foreclosures. In that extreme case approval standards would explain 100% of the crisis.

of the second period of the bust.[38] Specifically, we consider a first-order degradation of the income distribution indexed by $\zeta \in (0,1)$ among young mid-aged agents. For any $y \in Y^{\mathcal{Y}}$ or $y \in Y^{\mathcal{M}}$, an agent whose income is currently y remains at that income level with probability $1-\zeta$ but, in the complementary event, sees their income fall with equal probability to one of the lower income levels.

In other words, while agents make decisions thinking that the transition probability matrix between the first and the second period of the bust will be $P^{\mathcal{Y}}$ or $P^{\mathcal{M}}$ as expected, the actual transition matrix is the expected one convoluted with:

$$P^{\zeta} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \zeta & 1-\zeta & 0 & 0 \\ \frac{\zeta}{2} & \frac{\zeta}{2} & 1-\zeta & 0 \\ \frac{\zeta}{3} & \frac{\zeta}{3} & \frac{\zeta}{3} & 1-\zeta \end{bmatrix}.$$

Setting $\zeta = 0.31$ makes average household income $(y+ar)$ at the start of the second period of the bust 17.5% below what it was at the start of the first period. This matches the decline in average household real income in the US between 2007 and 2009 as estimated by Saez (2013).

Figure 10 shows the outcome of the experiment. The model now predicts defaults rates that remain near their peak for 4 years before beginning to show a significant decline that tracks available data closely. In either counterfactual experiment and in sharp contrast, the income shock has little impact on the path of default rates since there are much fewer negative equity loans in the stock when the income shock hits. Put another way, the frequency of high leverage loans magnifies the effect on default rates of the aggregate income shock much like they magnify the effect of the aggregate price shock.

[38] The fact that the change in the distribution is unexpected means we do not need to add more aggregate states.

6.4.3 Lower Interest Rates during the Boom

In our experiments, mortgage rates rise during the boom because the pool of borrowers becomes riskier and we leave the benchmark rate of interest unchanged throughout. In the data, mortgage rates fell during that period in large part because treasury rates fell. For instance, Freddie Mac's Primary Mortgage Survey Data for conventional loans with 20% downpayments suggest that real rates on HD loans fell by roughly 25% between 1999 and 2006. Consider then an experiment where we cut the risk-free rate and the cost of servicing loans proportionally until the boom stage in our transition experiment displays an average HD rate at origination that is 25% below its pre-98 level. Assume in addition that agents are surprised by the lower interest rates during the boom period. Specifically, assume that there are two boom states both featuring high home prices but one with HD rates 25% below their normal level while the other boom has the same risk-free rate and service cost as in the normal state. The transition probability function out of both boom states is the same as in our benchmark economy. Assume finally that agents think that the low interest boom is a zero-probability event.

Consider then a one-time transition to a low-interest boom that lasts 8 years as in our main experiment. As Figure 11 shows, this "perfect surprise" experiment produces essentially the same outcome as our main experiments with two exceptions. The share of LD loans in originations rises to a peak of 35% rather than 26% and home-ownership rates peak at around 74% rather than 72%. When home prices collapse back to their normal levels, the default rate rises to 252% above its pre-98 level. In the counterfactual, this increase in default rates is 68% smaller. Put another way, the quantitative bottom line of the experiment is essentially unchanged.[39]

[39] We also experimented with a scenario where agents expect all booms to feature low interest rates. Leaving all other parameters the same, that change in the environment turns out to raise home-ownership rates quite a bit in the pre-98 benchmark as agents now attach positive probability to the possibility that the rate of return on non-housing assets may be low in the future. To keep things comparable with our benchmark experiment then, we lowered the home-ownership premium (from 1.88 to 1.30) until home-ownership rates are at their data level in 1998. After making that change, all moments are once again near their data targets. In that recalibrated economy, the rise in home-ownership rate is not as pronounced during the boom as in the data.

Our model also predicts that the interest-rate spread between LD and HD rates should increase during the boom. This is because LD loans tend to be selected by riskier agents. In fact and as we discussed in the long-run section, LD loans selected by households with high assets and high income carry very similar rates as HD loans during the boom stage. In the SCF data we used to produce table 3, the gap in first-lien rates between borrowers whose CLTV is above 95% and those whose CLTV is below that threshold does go from a mere 7 basis points in 1998 to 45 basis points in 2007.[40] But more importantly perhaps, the key prediction of our model in this respect is that high-priced loans should become more prevalent during the boom and as we have already argued, that prediction is borne out by the relevant evidence.

7 The Role of Recourse

Throughout the paper, we have maintained the assumption that, in the event of default, the borrower's liability is limited to their home. In several states – known as anti-deficiency or non-recourse states – the law does in fact make it difficult for mortgage lenders to pursue deficiency judgments. The list of such states varies but generally includes Arizona, California, Florida (and sometimes Texas).[41] There are other states, known as "one-action" states, that allow the holder of the claim against the household to only file one lawsuit to either obtain the foreclosed property or to sue to collect funds. The list of such "nearly non-recourse" states includes Nevada and New York. Even in states where deficiency judgments are legal, conventional wisdom is that the costs associated with these judgments are so high, and the expected returns are so low, that recourse is seldom used.

Since new entrants tend to be asset-poor and riskier borrowers overall, the rise in the use of high-priced loans also becomes smaller as does the spike in default rates. When PTIs are left constant throughout, the overall rise in default rates is reduced by almost 50%.

[40] In our model, the spread between average rates on LD and HD loans reaches almost 300 basis points at the end of the boom but our rates are for the entire loan rather than simply the first one.

[41] See, for instance, http://www.helocbasics.com/list-of-non-recourse-mortgage-states-and-anti-deficiency-statutes.

Some empirical studies (see Ghent and Kudlyak , 2011) find that recourse decreases the probability of default when there is a substantial likelihood that a borrower has negative home equity. Table 7 compares long-run statistics in our pre-98 benchmark economy (which assumes no recourse) to their counterparts in the same economy with recourse. Specifically, in the event of default by a borrower with assets $a \geq 0$ and house size h, the intermediary collects $\min\{(1-\chi)q\epsilon h + a, b\}$ with recourse (as opposed to $\min\{(1-\chi)q\epsilon h, b\}$ without recourse), while the household retains $\max\{(1-\chi)q\epsilon h + a - b, 0\}$ with recourse (as opposed to $\max\{(1-\chi)q\epsilon h - b, 0\}$ without recourse). In other words, in the recourse economy, any asset the household owns at the time of default can be claimed as collateral by the lender. Recourse imposes a harsher punishment on borrowers, thus lowering the extensive default margin, and the higher repayment by borrowers lowers the intensive loss incidence margin to the lender. Both effects on these margins lead to lower interest rates.

As the table shows, this change in the environment greatly raises average recovery rates (from 50% to 92%) for obvious reasons. Conditional on a given set of characteristics at origination, the fact that default is a more costly option and the fact that recoveries are greater when default does happen make lenders willing to originate loans with a lower risk premium. With falling payments, it turns out that more agents are able and willing to enter mortgage markets and the home-ownership rate rises. While each loan is safer due to recourse, the pool of borrowers changes to allow more low income and low asset agents to enter. The net result on default rates is a decrease of about 10%.[42] In terms of welfare, agents are better off being born in an economy with recourse than without recourse. The fact that they are more likely to become homeowners outweighs the expected cost of broader recourse in the event of default. The consumption-equivalent distance between the two lifetime utilities is roughly half a percent for newly born agents assuming normal home prices at birth.

Could tougher recourse have mitigated the foreclosure crisis? To evaluate this possibility,

[42] Quintin (2012) discusses the interaction of the direct effect and composition effect of recourse in details. While broader recourse causes rates on loans to fall conditional on borrower characteristics at origination, the equilibrium effects on default are fundamentally ambiguous because broader recourse can enable riskier borrowers to obtain a mortgage. This is exactly what transpires in this experiment.

Figure 12 compares the baseline path of default rates during the transition to what the path would have been with recourse broadened to include ex-housing assets. With recourse access is already broad in the pre-98 benchmark hence the relaxation of approval standards has less impact making the increase in LD use more muted during the boom, as panel (b) shows. In addition, the frequency of high-priced (risky) loans rises much less during the boom. Not surprisingly then, the collapse in aggregate home values causes the spike in default rates to be lower, by roughly 20%.

We should emphasize that this result is obtained under the strong assumption that lenders can claim ex-housing assets fully and at no cost. In practice, even when households in foreclosure have other assets to claim, they also have opportunities to protect or dispose of them before they become subject to deficiency judgments. Our experiment should only be interpreted as saying that economies where recourse is broad and cost-effective in practice may in fact be less sensitive to aggregate home price shocks.

8 Conclusion

The calculations we present in this paper suggest that the rise in high leverage loans between 1999 and 2006 accounted for at least half of the foreclosure crisis. These findings raise two natural questions. First, did relaxed approval standards and higher leverage mortgages directly contribute to the run-up and eventual collapse in home-prices? Second, what caused the marked change in mortgage practices starting in 1999?

Our model takes the path of home prices as given. If high leverage mortgages contributed to the price collapse directly as well, their contribution to the crisis may be even greater than our numbers suggest. For instance, the availability of these mortgages may have led to some form of overbuilding as in Chatterjee and Eyigungor (2011). Their presence may also have contributed to the fragility and eventual freeze of the financial system, leading to a collapse of demand for housing, hence of housing prices. Formalizing and quantifying these ideas are promising avenues for future work, and should reinforce our main message: the rise of leverage played a significant role in the recent foreclosure boom.

As for what caused the change in the composition of mortgage originations starting in the late 1990s, or alternatively, the relaxation of approval standards, several explanations have been proposed. For instance, some view it as the natural consequence of the US government's effort to promote home-ownership over the past two decades, which included a loosening of the restrictions on what mortgages government-sponsored agencies could back or purchase. Our experiments are consistent with the idea that greater access to mortgage markets – whatever its cause – was a driving force behind the rise of home-ownership during the boom. Further research into endogenizing the timing and reasons for changes in approval standards will greatly enhance our understanding of the current foreclosure crisis.

A Algorithm

A.1 Mortgage market equilibrium

1. In the model, except for assets, all state variables are elements of finite sets. We discretize the asset space into twenty grid points between 0 and 10 times the median income level. The last value of the asset grid is chosen so that no households are constrained at the highest asset grid point. The asset grid is unevenly spaced. Specifically, every point of an equally spaced grid between 0 and $10^{2/3}$ is raised to the 3/2 power. This type of grid contains more points close to zero and offers better numerical performance.

2. Use value function iteration to find $V_O(a; s)$ from which we obtain savings decision rules for old agents.

3. Assuming $\gamma = 0$, obtain a candidate value function $V_M^R(a, y; s)$ from which we obtain savings decision rules for mid-aged renters.

4. Find the value function for mid-aged homeowners who have paid off their mortgage $V_M^{(\nu,\kappa)}(a, y, \epsilon, n \geq T; s)$ from which we obtain saving and home sales decision rules.

5. Calculate homeowners value functions where $n \in \{0, ..., T-1\}$.

   (a) To avoid calculating value functions for contracts which are not feasible for a given ν (say ν_0) and house size $\widehat{h}$ (say h_0) with $\kappa = (\widehat{a}, \widehat{y}, h_0; \widehat{s})$ (i.e. to ensure $\nu_0 \in K$), check if the household in that state has enough assets to make a downpayment (i.e. constraint (3.1) is satisfied) and that if the mortgage rate is given by $r_i^{\nu_0}(\kappa)$, the implied mortgage payment meets the PTI requirement (i.e. constraint (3.2) is satisfied). As an initial guess, let $r_0^{\nu_0}(\kappa) = r + \phi$.

   (b) For each feasible ν_0 and h_0, use backward induction starting from $V_M^{(\nu,\kappa)}(a, y, \epsilon, h_0, n = T-1; s)$ to obtain $V_M^{(\nu,\kappa)}(\widehat{a}, \widehat{y}, 1, \widehat{h}, n = 0; s)$. This step also yields saving, default, and sale decision rules for $n \in \{1, ..., T-1\}$ and optimal mortgage choices at $n = 0$.

(c) Calculate $W_0^{(\nu,\kappa)}(\widehat{a}, \widehat{y}, \widehat{\epsilon} = 1; \widehat{s})$ given the resulting decision rules.

(d) If the present value of $W_0^{(\nu,\kappa)}(\widehat{a}, \widehat{y}, \widehat{\epsilon} = 1; \widehat{s})$ is less than the initial loan size, increase the interest rate by a small amount and repeat this step. Otherwise, the equilibrium interest rate is found.

6. Find $V_Y(a, y; s)$ from which we obtain asset decision rules for young agents. Because of a potential discontinuity caused by the downpayment requirements, the value functions for young agents are solved for by grid search (all others use interpolation).

7. Compute a long run cross-sectional distribution for any s by starting at normal times, with zero assets, using the invariant distribution of income for the young and find the sequence of distributions given in section B.

In the computations we summarize in footnote 20, we being with the mortgage market equilibrium that obtains for $\gamma = 0$. We then update all value and policy functions for strictly positive values of γ holding the interest rate schedule the same as in the equilibrium with $\gamma = 0$. Solving for a full mortgage market equilibrium when $\gamma > 0$ would entail the following basic steps:

1. Guess an entire mortgage schedule (i.e. a rate for all possible loans and borrower characteristics) for mid-aged agents who get the option to buy a home.

2. Solve for all value and policy functions, and for intermediary profits.

3. Update the whole schedule until profits are zero in expected terms on all contracts.

The key difference from the simpler ($\gamma = 0$) algorithm is that agents' decisions now depend on the expectations they have as to what rates will prevail when they get another chance to become a homeowner in the future which in turn depends on what their characteristics will be when that option arrives. Instead of solving for equilibrium rates on a contract-by-contract basis, it becomes necessary to find a fixed point on the set of all possible mortgage schedules.

A.2 Transition Dynamics

1. Begin with the benchmark equilibrium distribution generated with a long sequence $s_t = N$ such that the distribution difference from another N draw of the aggregate shock is below double precision.

2. Use the operators in section B to compute $\mu_{\mathcal{Y}}^{t+1}(A', y'|s^t)$, $\mu_{\mathcal{M},R}^{t+1}(A', y'|s^t)$, $\mu_{\mathcal{M},n=0}^{t+1}(A', y'|s^t)$, $\mu_{\mathcal{M},n\geq 1}^{t+1}(A', y', \epsilon', n', \widehat{\nu}, \widehat{\kappa}|s^t)$, and $\mu_{\mathcal{O}}^{t+1}(A'|s^t)$ with aggregate shock $s_{t+1} = H$.

3. Repeat step 2 for $s_{t+2} = s_{t+3} = s_{t+4} = H$ and $s_\tau = N$ for $\tau > t + 4$.

B Cross-sectional distributions

The set of possible histories of aggregate shocks up to date t is S^t. An element $s^t \in S^t$ implies a path for home prices, approval standards and rental rates. Now recall that old households who die are immediately replaced by young households. Therefore, the transition matrix across ages is effectively given by:

$$\begin{bmatrix} (1-\rho^M) & \rho^M & 0 \\ 0 & (1-\rho^O) & \rho^O \\ \rho^D & 0 & 1-\rho^D \end{bmatrix}.$$

Let $(\psi^{\mathcal{Y}}, \psi^{\mathcal{M}}, \psi^{\mathcal{O}})$ be the corresponding invariant distribution of ages. Making the mass of agents born each period $\mu^0 \equiv \psi^{\mathcal{O}}\rho^D$ normalizes the total population size to one. Recall in addition that newborns start their life with no assets and that their income is drawn from the unique invariant income distribution p^0 associated with $P^{\mathcal{Y}}$.

There are five fundamental types of agents in our environment. Old agents are distributed over the set of possible assets

$$\Omega^{\mathcal{O}} = I\!R_+.$$

Denote the distribution of individual states for old households at the start of date t given a history s^{t-1} of aggregate shocks up to the preceding period by

$$\mu^t_{\mathcal{O}}(\cdot|s^{t-1}) : B\left(\Omega^{\mathcal{O}}\right) \mapsto [0,1]$$

where $B\left(\Omega^{\mathcal{O}}\right)$ is the set of Borel measurable subsets of $\Omega^{\mathcal{O}}$. By convention, we will define this and all state distributions at a given date after all shocks are realized but before housing choices are made.

Young agents are distributed on the following set of possible states:

$$\Omega^{\mathcal{Y}} = \left\{(a, y) \in I\!R_+ \times Y^{\mathcal{Y}}\right\}.$$

Denote by $\mu^t_{\mathcal{Y}}(\cdot|s^{t-1})$ the corresponding cross-sectional distribution of individual states for the young given a history s^{t-1} of past shocks.

Mid-aged renters and mid-aged households with the option to buy ($n = 0$) are distributed over the same asset-income space

$$\Omega^{\mathcal{M},R} = \Omega^{\mathcal{M},n=0} = \left\{(a, y) \in I\!R_+ \times Y^{\mathcal{M}}\right\}$$

and we denote their respective history-conditional distributions at date t by $\mu^t_{\mathcal{M},R}(\cdot|s^{t-1})$, and $\mu^t_{\mathcal{M},n=0}(\cdot|s^{t-1})$.

The fifth and final type of agents are mid-aged homeowners. Their state includes not only their asset and income position, but also their idiosyncratic house price shock (ϵ), their mortgage type (κ, ν) and the age (n) of their contract. The corresponding space is:

$$\Omega^{\mathcal{M},n\geq 1} = \left\{(a, y, \epsilon, n, \nu, \kappa) \in I\!R_+ \times Y^{\mathcal{M}} \times \mathcal{E} \times I\!N_{++} \times \{LD, HD\} \times \mathcal{K}\right\}$$

where $\mathcal{K} = \left\{I\!R_+ \times Y^{\mathcal{M}} \times \{h^2, h^3\} \times S\right\}$ is the set of possible mortgage characteristics at origination. Let $\mu^t_{\mathcal{M},n\geq 1}(\cdot|s^{t-1})$ be the associated distribution.

With this notation in hand, we can define transition functions for distributions of individual states. Consider first the young. Let A' be any Borel subset of $I\!R_+$ and pick any $y' \in Y^{\mathcal{Y}}$. An agent is young at the start of a period if: (i) they were just born; or (ii) they were young in the previous period and did not age. It follows that for any t,

$$\mu_{\mathcal{Y}}^{t+1}(A', y'|s^t) = \mu^0 p^0(y') 1_{\{0 \in A')\}} + (1 - \rho^M) \int_{\omega \in \Omega^{\mathcal{Y}}} 1_{\{a'_{\mathcal{Y}}(\omega; s^t) \in A')\}} P^{\mathcal{Y}}(y'|y) d\mu_{\mathcal{Y}}^t(\omega|s^{t-1}). \quad \text{(B.1)}$$

Here, $a'_{\mathcal{Y}}(\omega; s^t)$ is the agent's savings choice given his individual state $\omega = (a, y) \in \Omega^{\mathcal{Y}}$ and aggregate history $s^t \in S^t$. Transitions are similarly defined for the old and we omit them for conciseness.

Agents are mid-aged renters at the start of a given period if: (i) they were mid-aged renters, did not get the option to buy, and did not age, (ii) if they had the option to become homeowners in the previous period, chose to forego that option, and did not age, or, (iii) were mid-aged homeowners but chose to sell or default. For any measurable subset (A', y') of $\Omega^{\mathcal{M},R}$ and history, the transition is given by

$$\begin{aligned} \mu_{\mathcal{M},R}^{t+1}(A', y'|s^t) &= (1 - \rho^O)(1 - \gamma) \int_{\omega \in \Omega^{\mathcal{M},R}} 1_{\{a'_{\mathcal{M},R}(\omega; s^t) \in A')\}} P^{\mathcal{M}}(y'|y) d\mu_{\mathcal{M},R}^t(\omega|s^{t-1}) \\ &+ (1 - \rho^O) \int_{\{\omega \in \Omega^{\mathcal{M},n=0} : h_{\mathcal{M},n=0}(\omega; s^t) = h^1\}} 1_{\{a'_{\mathcal{M},n=0}(\omega; s^t) \in A')\}} P^{\mathcal{M}}(y'|y) d\mu_{\mathcal{M},n=0}^t(\omega|s^{t-1}) \\ +(1 - \rho^O) &\int_{\{\omega \in \Omega^{\mathcal{M},n \geq 1} : (D+S)(\omega; s^t) = 1\}} 1_{\{a'_{\mathcal{M},n \geq 1}(\omega; s^t) \in A')\}} P^{\mathcal{M}}(y'|y) d\mu_{\mathcal{M},n \geq 1}^t(\omega|s^{t-1}). \quad \text{(B.2)} \end{aligned}$$

Here, $h_{\mathcal{M},n=0}(\omega; s^t)$ is the household's housing choice given its individual state $\omega = (a, y) \in \Omega^{\mathcal{M},n=0}$ and aggregate history $s^t \in S^t$.

Households start a period with the option to buy if: (i) they were mid-aged renters in the previous period and received the option to buy; or (ii) if they just became mid-aged. This gives, for any measurable subset (A', y') of $\Omega_{\mathcal{M},n=0}$ and history,

$$\begin{aligned} \mu_{\mathcal{M},n=0}^{t+1}(A', y'|s^t) &= (1 - \rho^O)\gamma \int_{\omega \in \Omega^{\mathcal{M},R}} 1_{\{a'_{\mathcal{M},R}(\omega; s^t) \in A')\}} P^{\mathcal{M}}(y'|y) d\mu_{\mathcal{M},R}^t(\omega|s^{t-1}) \\ &+ \rho^M \int_{\omega \in \Omega^{\mathcal{Y}}} 1_{\{a'_Y(\omega; s^t) \in A')\}} P^{\mathcal{Y}}(y'|y) d\mu_{\mathcal{Y}}^t(\omega|s^{t-1}) \quad \text{(B.3)} \end{aligned}$$

Finally, the cross-sectional distribution of homeowners evolves according to whether they were: (i) homeowners in the previous period and did not age or choose to sell or default; or (ii) were given the option to buy, took it, and did not change age state. Consider any Borel subset A' of $I\!R_+$, $y' \in Y^{\mathcal{M}}$, $\varepsilon' \in \mathcal{E}$, $n' \in I\!N_{++}$, $\widehat{\nu} \in \{LD, HD\}$ and $\widehat{\kappa} = (\widehat{a}, \widehat{y}, \widehat{h}; \widehat{s}) \in \mathcal{K}$ at any date t and in any history s^t. Denote by $\Omega_n^{(\kappa,\nu)}$ the subset of $\Omega^{\mathcal{M},n\geq 1}$ of homeowners with mortgage characteristics (κ, ν) and mortgage age $n \in I\!N$. Then,

$$\mu^{t+1}_{\mathcal{M},n\geq 1}(A', y', \epsilon', n', \widehat{\nu}, \widehat{\kappa}|s^t) =$$

$$(1-\rho^O) \times \Bigg\{ \int_{\Omega^{(\kappa,\nu)}_{n'-1}} 1_{\{a'_{\mathcal{M},n\geq 1}(\omega;s^t)\in A', h_{\mathcal{M},n\geq 1}(\omega;s^t)=\widehat{h}\}} P^{\mathcal{M}}(y'|y) P^{\epsilon}(\epsilon'|\epsilon) d\mu^t_{\mathcal{M},n\geq 1}(\omega|s^{t-1})$$
$$+ \int_{\Omega^{\mathcal{M},n=0}} 1_{\{n'=1, a'_{\mathcal{M},n=0}(\omega;s^t)\in A', (D+S)(\omega;s^t)=0, \nu_{\mathcal{M},n=0}(\omega;s^t)=\widehat{\nu}, s^t_t=\widehat{s}\}} P^{\mathcal{M}}(y'|y) P^{\epsilon}(\epsilon'|1) d\mu^t_{\mathcal{M},n=0}(\omega|s^{t-1}) \Bigg\} \tag{B.4}$$

where s_t^t is the date t realization of aggregate shock history s^t.

C Competing hazard model

To document more systematically the effects of selection and equity effects on default, we generated a random sample of 50,000 loans originated at the steady state that follows a large number of boom periods. Results for pseudo-panels generated in the pre-98 benchmark are similar. We then estimated a competing risk model with the following covariates for borrower $i \in \{1, \ldots, 50000\}$:

1. the mortgage type ($1_{LD,i} = 1$ if the borrower selects a zero-downpayment loan, 0 otherwise);
2. the loan-to-income ratio at origination (LTY_i);
3. the asset-to-loan ratio at origination (ATL_i);

4. a measure $HE_{i,n} \equiv h\epsilon_{i,n}q_H - b_n$ of home-equity on each loan at each possible age $n = 0, \ldots 14$ where ϵ_n is the value of the idiosyncratic value shock on loan i in period n while b_n is the loan balance;

5. the income $INC_{i,n}$ of borrower i in period n.

Note that the first three covariates are fixed at origination while the last two covariates vary with loan age.

Let $\xi^e_{n,i}$ be the hazard rate at loan age n for homeowner i due to event $e \in \{D, S\}$, where D stands for default while S stands for sale. We adopt a standard Cox proportional hazard specification for hazard rates, namely:

$$\xi^e_{n,i} = H\left(\omega^e_n \times \exp\left\{\beta^e_{LD} 1_{LD,i} + \beta^e_{LTY} LTY_i + \beta^e_{ATL} ATL_i + \beta^e_{HE} HE_{n,i} + \beta_{INC} INC_{n,i}\right\}\right),$$

where $H(x) = \exp(-\exp x)$ for all $x > 0$, and ξ^e_n is the baseline hazard rate at loan age n.

Table 8 shows the result of the estimation. As expected, estimated hazard rates into default rise with loan-to-income at origination and fall with the asset-to-loan ratio. Income and home equity have a negative impact on both hazards. After controlling for all these characteristics, the loan type dummy actually has a negative effect on default. This suggests that loan selection contributes to increased default rates mainly through its consequences on equity accumulation and on the distribution of income among mortgage holders.

Most of the empirical literature on default rates adopts a version of this proportional hazard specification. It is difficult to compare our results directly to the outcomes of these studies because they usually control for covariates that have no clear counterpart in our model, and usually lack detailed information on borrower assets. Gerardi et al., 2009, for instance, include proxies for county-level economic and state-wide house price conditions, but do not control for assets at origination. Still, theirs and most other papers find as we do that high LTVs at origination and high debt-to-income ratios have a significant effect on default rates as do proxies for home equity and borrower income.

D Determinants of mortgage rates at origination

Table 9 shows that over half of the equilibrium variation in yields can be accounted for by loan and borrower characteristics at origination in the long boom economy. Once again using our representative sample of 50,000 mortgages to regress log mortgage rates on assets, income and loan size at origination yields an R^2 of nearly three-quarters. Furthermore, higher assets and income are associated with lower yields since they reduce the likelihood of default. A higher loan size at origination, however, is associated with a lower rate because large loans tend to be selected by agents with high assets and high income. In our parameterization, this selection effect turns out to more than offsets the fact that large loans obviously involve larger payments.

By way of comparison, consider the 2007 sample of recent home-buyers in the SCF we used to produce table 3. Among those buyers, interest rates on first mortgages are negatively correlated with reported income, with loan size and with net worth, with the first two correlations being statistically significant. Running the regression displayed in the table yields coefficients with the right (negative) sign but only income is significant at conventional levels. Furthermore and not surprisingly given the heterogeneity among SCF borrowers and loans which our model does not contain, the R^2 in that regression is low.

E The Gerardi, Shapiro, and Willen (2009) counterfactual

Gerardi et. al (2009) use their econometric model to measure the potential role of changes in mortgages practices during the boom using the following counterfactual approach. They subject borrowers in their data sample who took a loan in 2002 to the same price history as their 2006 counterparts and find (see Figure 10) that 2002 loans would have defaulted at approximately half the rate of their 2005 counterparts.

To run a similar counterfactual with our model, consider an experiment where there is no change in approval standards and home prices during the boom so that the boom period is now nothing but another four periods of normal times. At the onset of the crisis then, the distribution of borrowers is exactly what it was in 1998, before approval standards change. The importance of high-leverage loans, in particular, remains at 7% until the crisis strikes. In late 2006, we subject those borrowers to a fall in home values from q_N to q_L (which is a fall of roughly 30% in aggregate values, much like in the baseline experiment.) Figure 13 shows the outcome of this experiment (counterfactual 2) compared with the counterfactual we discussed in the text (counterfactual 1.) In this second counterfactual, foreclosure rates rise by 164%, so that the overall increase in default rates is about 40% lower than in our baseline experiment, which is similar to what Gerardi et. al (2009) found using their econometric approach.

We view these two approaches as complementary and find it reassuring that they yield similar quantitative answers. The empirical approach is conditional on the econometric structure used to estimate the elasticity of default decisions to price shocks. The outcome of our counterfactual experiment likewise depends on the modeling assumptions we make, but, conditional on that economic structure, the effect of different price and underwriting scenarios on default can be measured exactly.

Why does the second counterfactual suggest a role for LD loans that is significantly lower than what the first counterfactual suggests? Once again, the answer is selection. Keeping approval standards the same, the increase in price causes home-ownership rates to drop. Intuitively, agents who became home-owners during the boom in the benchmark experiment but choose to remain renters in the first counterfactual tend to have lower income and assets than those households who buy regardless of approval standards. In the first counterfactual therefore, only the safest households remain in mortgage markets and those households, as we have repeatedly discussed in this paper, are more likely to opt for HD loans and are less prone to payment difficulties.

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Table 1: **Benchmark parameters**

Parameters determined independently			*Parameters determined jointly*		
ρ^M	Fraction of young agents who become mid-aged	1/7	θ	Owner-occupied premium	1.877 (0.386)
			β	Discount rate	0.876 (0.007)
ρ^O	Fraction of mid-aged agents who become old	1/12	$\alpha_N (= \alpha_L)$	PTI level in normal (low) state	0.182 (0.099)
			ϕ	Mortgage service cost	0.050 (0.025)
ρ^D	Fraction of old agents who die	1/10	χ	Foreclosing costs	0.460 (0.021)
			h^1	Size of rental unit	1.000 (N.A.)
r	Storage return	8%	h^2	Size of small house	1.023 (0.035)
δ	Maintenance rate	5%	h^3	Size of large house	1.569 (0.063)
ν^{HD}	High downpayment	20%	λ	Home-value shock probability	0.228 (0.201)
T	Mortgage maturity	15	$\tilde{\epsilon}$	Size of home value shock	0.326 (0.000)
$\frac{q_L}{q_N}$	Low home value level	0.7	q_N	Normal home value level	1.016 (0.000)
$\frac{q_H}{q_N}$	High home value level	1.45			

Notes: Standard errors based on 100 repetitions and 7,000 households are in parenthesis for jointly determined parameters except for the size of rental units which is normalized to one.

Table 2: Targeted moments

	Pre-98 data	Pre-98 benchmark	Long-term moments
Home-ownership rate	0.66	0.66	0.69 (0.061)
Ex-housing asset to income ratio	1.41	1.57	1.56 (0.023)
Housing expenditure share	0.15	0.15	0.15 (0.001)
Rent to income ratio	0.45	0.48	0.48 (0.001)
Homeowner housing share	0.173	0.174	0.173 (0.020)
Interest rate on HD loans	0.145	0.141	0.141 (0.004)
Foreclosure rate	1.45	1.42	1.62 (0.007)
Foreclosure discount	0.75	0.75	0.76 (0.052)
Recovery rate	0.50	0.50	0.49 (0.025)
Fraction of LD loans	0.07	0.07	0.12 (0.082)
Standard error of 2-year capital gains	0.22	0.22	0.22 (0.000)

Note: Pre-98 moments are evaluated at the distribution of households states that follows a infinite draw of normal aggregate shocks. Long-term moments are the average value of each moment for a 3,000-period sequence of aggregate shocks drawn from P^q and starting from the pre-98 benchmark distribution of household states. Standard deviations for the same history of shocks are in parenthesis.

Table 3: Cross-sectional Predictions

	1998 survey				**2007 survey**				**2010 survey**			
	LTY		High-LTV		LTY		High-LTV		LTY		High-LTV	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Income												
Below median	1.27	0.82	0.16	0.14	1.92	1.94	0.21	0.40	1.57	1.17	0.22	0.25
	(0.04)		*(0.02)*		*(0.06)*		*(0.01)*		*(0.06)*		*(0.01)*	
Above median	0.71	0.44	0.10	0.00	1.07	0.72	0.10	0.12	1.01	0.63	0.21	0.00
	(0.01)		*(0.01)*		*(0.02)*		*(0.01)*		*(0.02)*		*(0.01)*	
Asset-to-income												
Below median	0.95	0.65	0.19	0.14	1.49	1.27	0.22	0.52	1.17	0.95	0.28	0.25
	(0.02)		*(0.02)*		*(0.04)*		*(0.02)*		*(0.03)*		*(0.02)*	
Above median	0.97	0.62	0.08	0.00	1.47	1.38	0.09	0.00	1.38	0.86	0.14	0.00
	(0.02)		*(0.01)*		*(0.04)*		*(0.01)*		*(0.05)*		*(0.01)*	
Age												
Below 35	0.99	0.63	0.17	0.10	1.60	1.31	0.24	0.34	1.24	0.62	0.25	0.18
	(0.03)		*(0.02)*		*(0.04)*		*(0.02)*		*(0.04)*		*(0.02)*	
Above 35	0.95	0.64	0.11	0.03	1.37	1.37	0.10	0.12	1.30	0.63	0.18	0.04
	(0.02)		*(0.01)*		*(0.04)*		*(0.01)*		*(0.04)*		*(0.01)*	
Loan size												
Below median	0.79	0.52	0.06	0.11	1.08	1.09	0.16	0.14	0.89	0.53	0.16	0.18
	(0.03)		*(0.02)*		*(0.03)*		*(0.01)*		*(0.02)*		*(0.01)*	
Above median	1.10	0.75	0.21	0.04	1.79	1.31	0.15	0.39	1.57	0.72	0.26	0.08
	(0.02)		*(0.01)*		*(0.04)*		*(0.01)*		*(0.05)*		*(0.01)*	

Note: All numbers are for purchase loans originated in the two years preceding each survey to households whose head is younger than 65. LTY entries are the average loan-to-income ratio in each categories and include all reported liens. High-LTV entries are the fraction of contracts with cumulative leverage in excess of 95% of reported home value. SCF sample weights are used throughout, standard errors are in parentheses. In the model, "Below 35 years" refers to homeowners who become middaged after 12 periods of youth or fewer.

Table 4: Housing and mortgage decisions by asset and income

		Rent	LD loan		HD loan	
		h^1	h^2	h^3	h^2	h^3
	y^1	all a_0	-	-	-	-
Normal state	y^2	$a_0 < 2.24$	-	-	$2.24 \leq a_0$	-
	y^3	-	$a_0 < 0.34$	-	-	$0.34 \leq a_0$
	y^4	-	-	$a_0 < 0.34$	-	$0.34 \leq a_0$
	y^1	$a_0 < 0.97$	-	-	$0.97 \leq a_0 < 2.73$	$2.73 \leq a_0$
Boom state	y^2	$a_0 < 0.12$	$0.12 \leq a_0 < 0.34$	-	$0.34 \leq a_0 < 0.63$	$0.63 \leq a_0$
	y^3	-	-	$a_0 < 0.63$	-	$0.63 \leq a_0$
	y^4	-	-	$a_0 < 0.63$	-	$0.63 \leq a_0$

Table 5: Default rates by borrower type

	LD loans	HD loans	All loans
pre-1998			
Fraction of stock	6.99	93.01	100.00
Default rate	2.30	1.36	1.42
First period of the crisis			
Fraction of stock (ξ_t^ν)	13.92	86.08	100
Default rate (D_t^ν)	14.69	3.82	5.33
Incumbents			
Fraction of stock	8.16	79.37	87.53
Default rate	7.46	2.71	3.15
Switchers			
Fraction of stock	4.47	0.00	4.47
Default rate	10.28	N.A.	10.28
New-entrants			
Fraction of stock	1.29	6.71	8.00
Default rate	64.46	16.91	24.59

Note: All entries are model predictions. New entrants are borrowers who took their loan during the boom and, given their characteristics at origination, would have been renters in the pre-98 economy. Loan-type switchers are boom-stage borrowers who would have opted for a different loan type in the pre-98 economy. Incumbents are all other home-owners in the first period of the crisis.

Table 6: Default by category

	Fraction of all defaults			Average equity at default		
	Income shock	Moving shock	Neither	Income shock	Moving shock	Neither
Pre-98						
LD loan	17.32%	77.92%	4.76%	-5.15%	-29.74%	-5.19%
HD loan	9.63%	90.37%	0.00%	6.67%	-9.03%	N.A.
Boom						
LD loan	62.23%	14.80%	22.93%	-14.82%	-43.26%	-19.10%
HD loan	28.85%	71.15%	0.00%	-13.95%	-13.33%	N.A.
Bust						
LD loan	44.65%	37.85%	17.49%	-47.76%	-47.51%	-49.53%
HD loan	27.75%	68.85%	0.00%	-19.18%	-28.81%	N.A.

Note: All entries are model predictions. In the right-hand panel of the table, average equity (=home value minus loan balance) is calculated as the average fraction of home value for each loan type and default category.

Table 7: The long-run effects of recourse

	Pre-98 benchmark	Pre-98 benchmark with recourse
Home-ownership rate	0.66	0.74
Interest rate on HD loans	0.141	0.132
Interest rate on LD loans	0.147	0.134
Foreclosure discount	0.75	0.73
Recovery rate	0.50	0.92
Fraction of LD loans	0.07	0.06
Foreclosure rate	1.42	1.28

Table 8: Determinants of mortgage termination

Covariate	Default		Sale	
LD indicator	-0.5553	(0.0380)	-0.3419	(0.0212)
Loan to Income Ratio	0.4664	(0.0133)	0.8054	(0.0116)
Assets to Loan Ratio	-0.4192	(0.0301)	-0.1502	(0.0168)
Income	-0.8926	(0.0158)	-0.5338	(0.0119)
Home equity	-8.2527	(0.0925)	-0.4872	(0.0166)

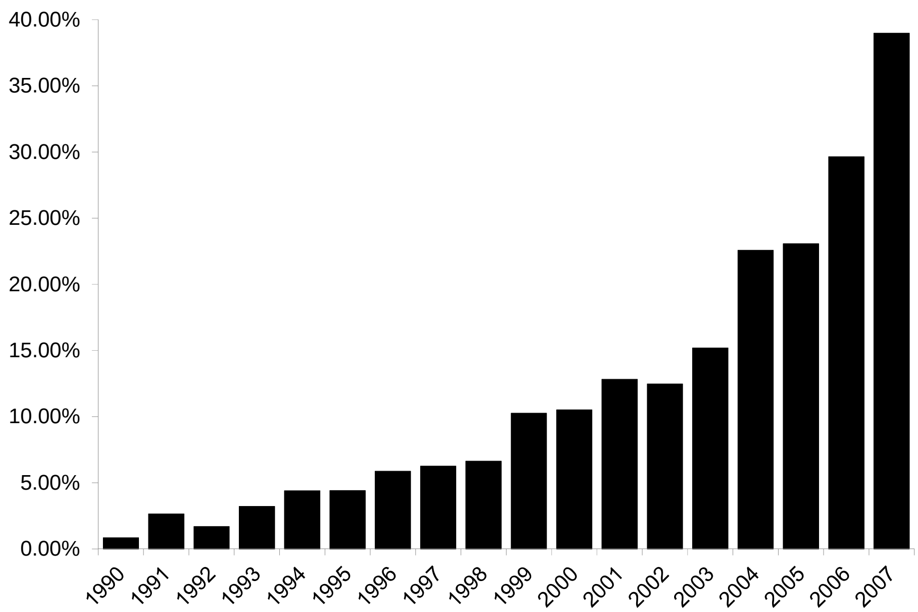
Note: Bootstrapped standard errors (based on 200 replications) are in parenthesis; log likelihood= -285818.42*; all coefficients are significant at the 1% level. We estimate the model using method A in Lunn and McNeil, 1995.*

Table 9: Determinants of log mortgage rates

Covariate	Coefficient	
Constant	-1.3900***	(0.0043)
Assets at origination	-0.0852***	(0.0006)
Income at origination	-0.1050***	(0.0007)
Loan size	-0.0447***	(0.0023)

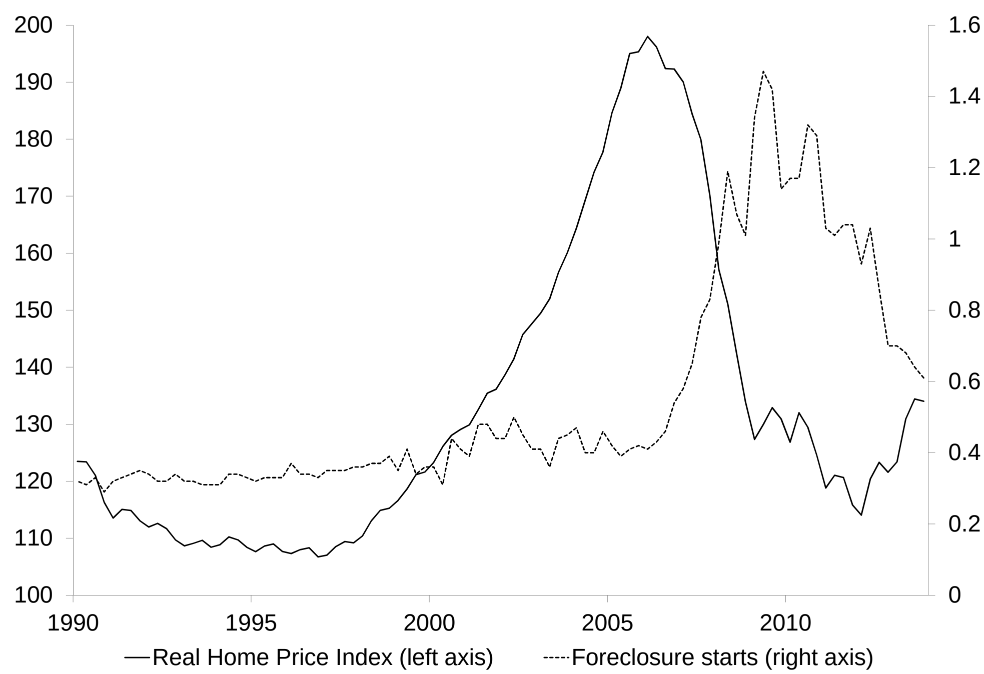
Notes: Standard errors are in parentheses; $R^2 = 0.54$*; *** significant at 1% level*

Figure 1: FHA and GSE purchase loans with a cumulative LTV above 97%



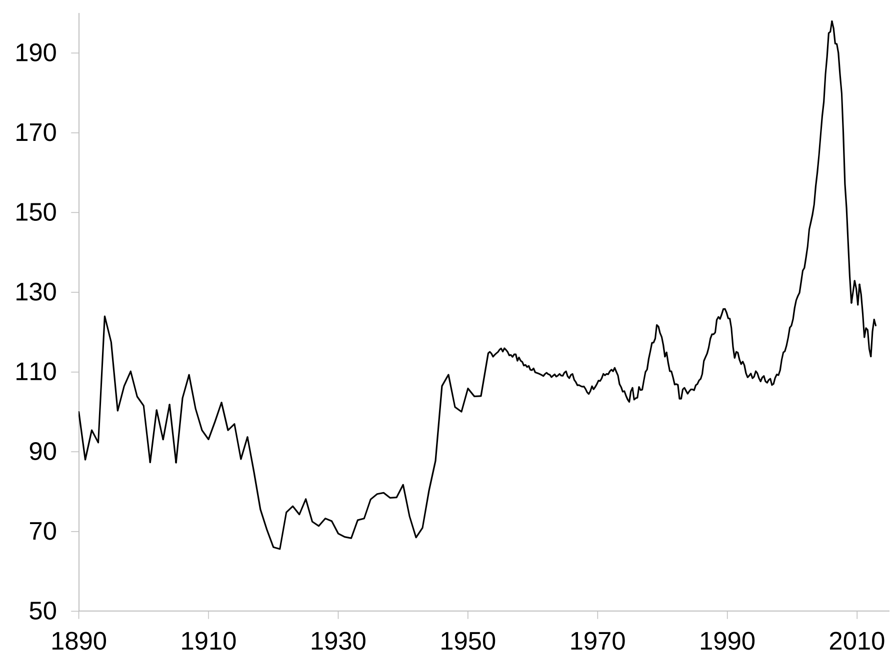
Source: Pinto (2010). Fannie Mae's purchase loans are the proxy for conventional loans. FHA loans are classified according to the first mortgage's size only.

Figure 2: The housing boom and bust



Source: The real home price index is the US S&P/Case-Shiller Index. Foreclosure starts are from the Mortgage Bankers Association's National Delinquency Survey and are the reported number of mortgages for which foreclosure proceedings are started in a given quarter divided by the initial stock of mortgages.

Figure 3: Real US home price index since 1890



Source: Shiller (2000), updated data available at http://www.econ.yale.edu/ shiller/data.htm.

Figure 4: Distribution of assets upon entering mid-age

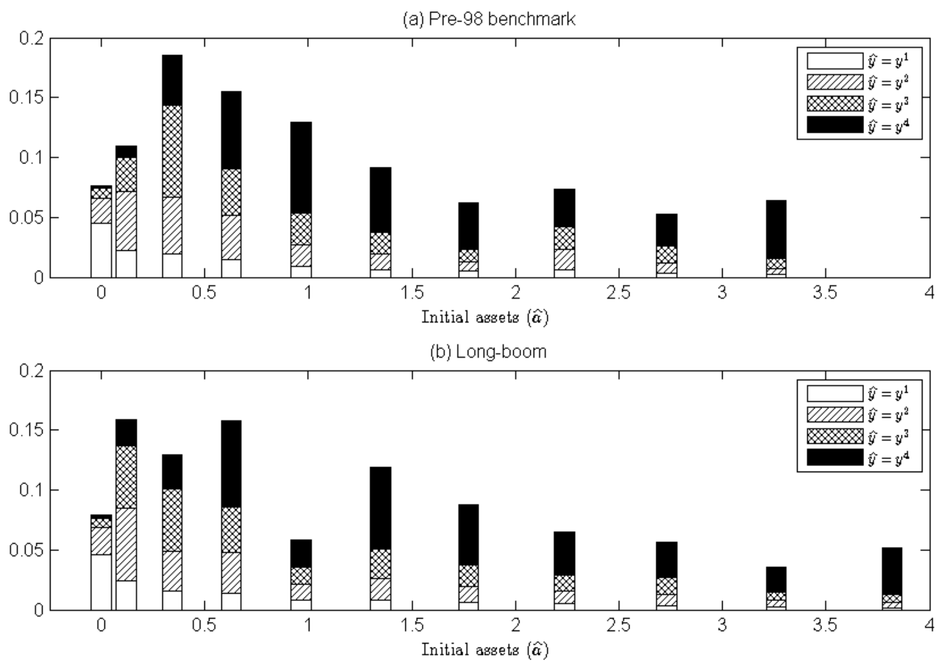


Figure 5: Average default hazard rates

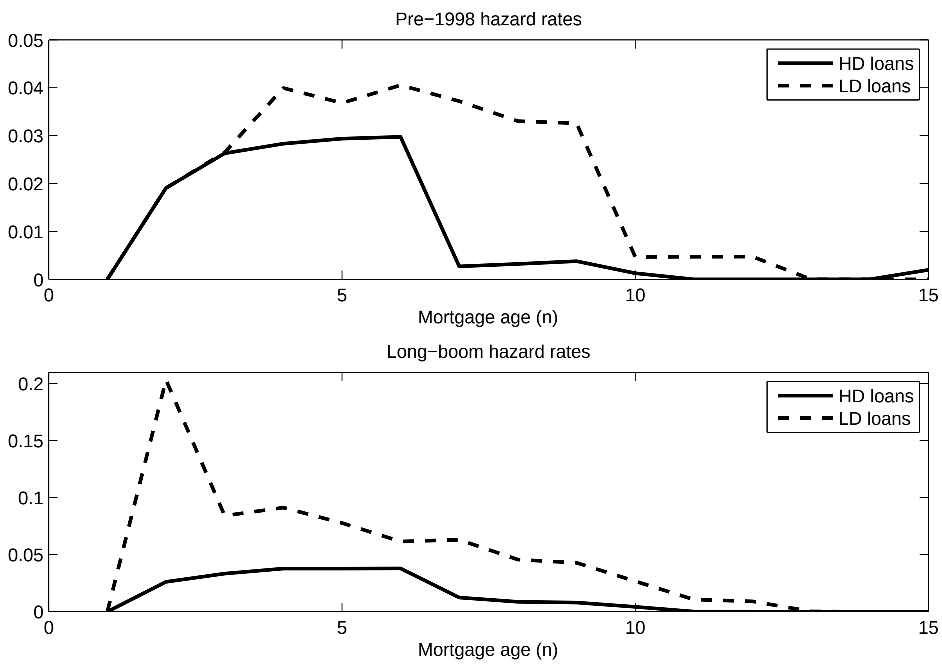


Figure 6: Equilibrium interest rate schedules in the boom state

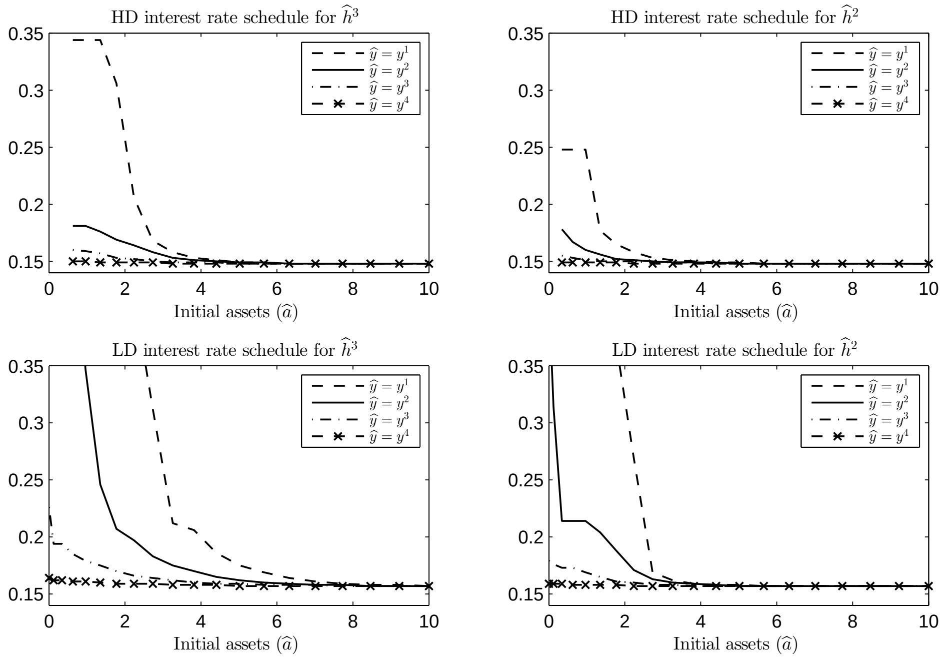


Figure 7: Distribution of equilibrium interest rates

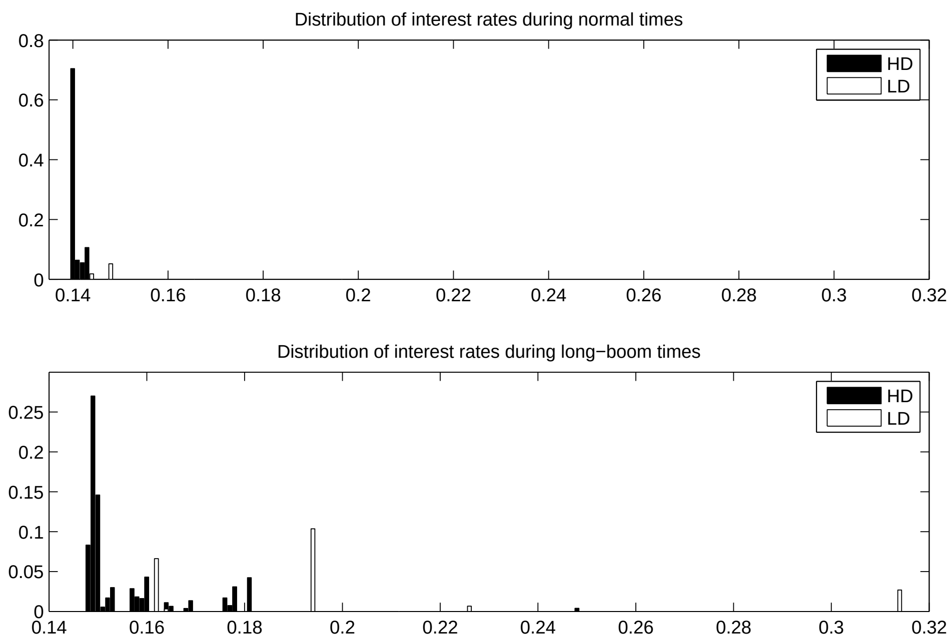
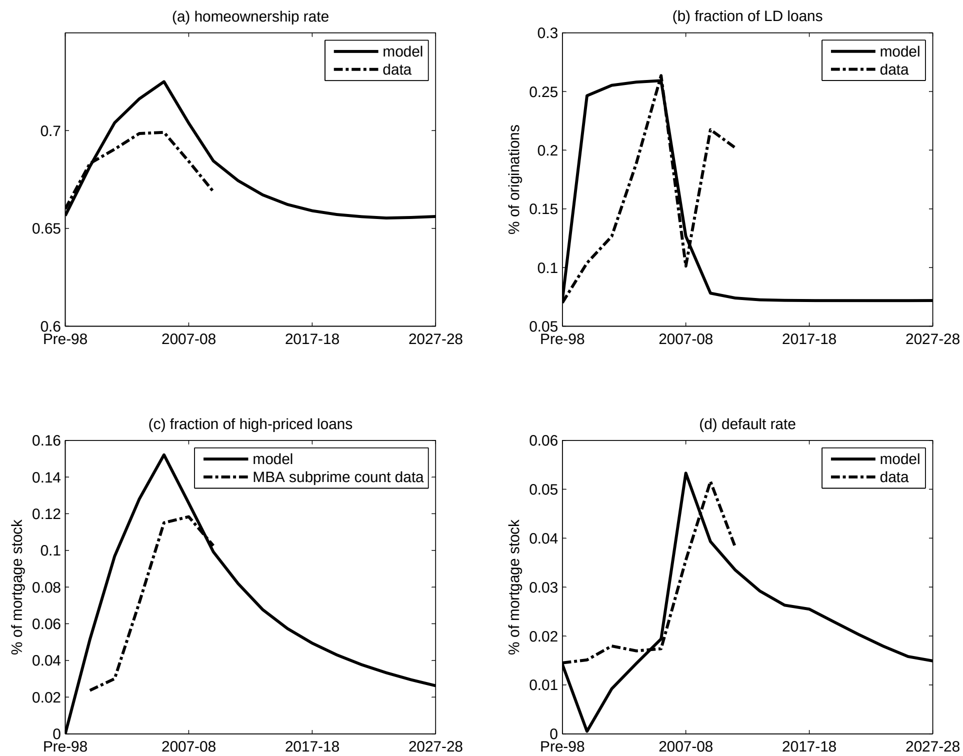


Figure 8: The boom-bust



Notes: Data on home-ownership rates are for households whose head is between 30 and 55 years old as estimated by the Census Bureau. The fraction of LD loans is from Pinto (2010, see Figure 1) until 2006 and roughly estimated as two-thirds of FHA's share of purchase originations for 2007-10. The fraction of high-priced loans is compared to the fraction of subprime mortgages in the stock of mortgages covered by the MBA's National Delinquency Survey. Default rates are computed from that same survey as described in the parameterization section.

Figure 9: Leverage counterfactual

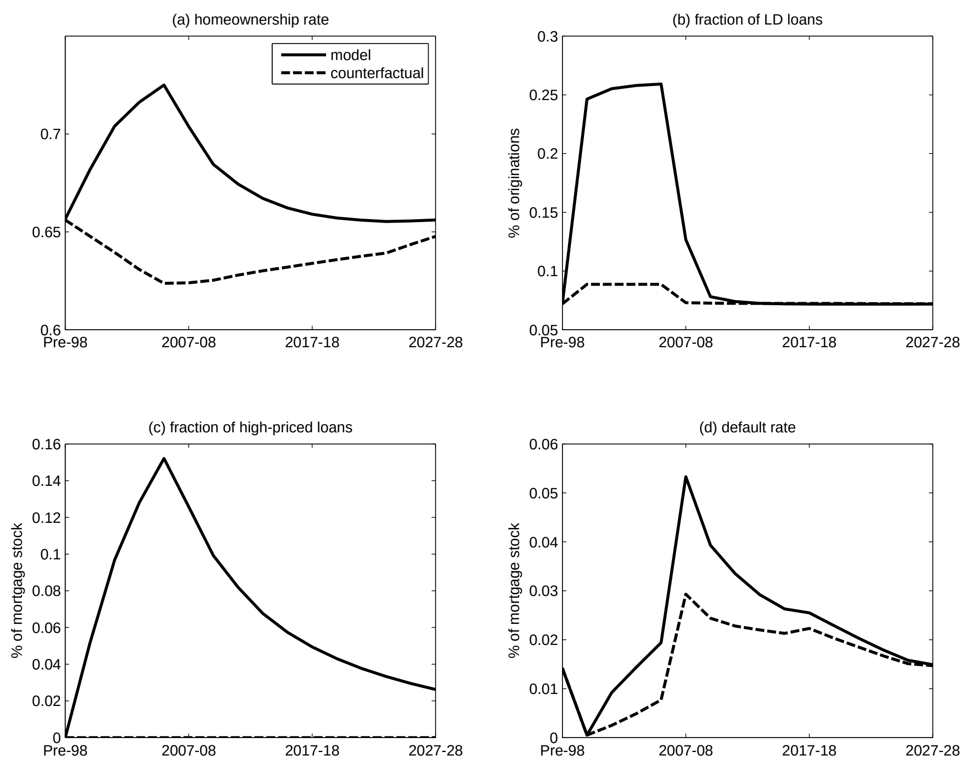


Figure 10: Aggregate income shock in second period of the crisis

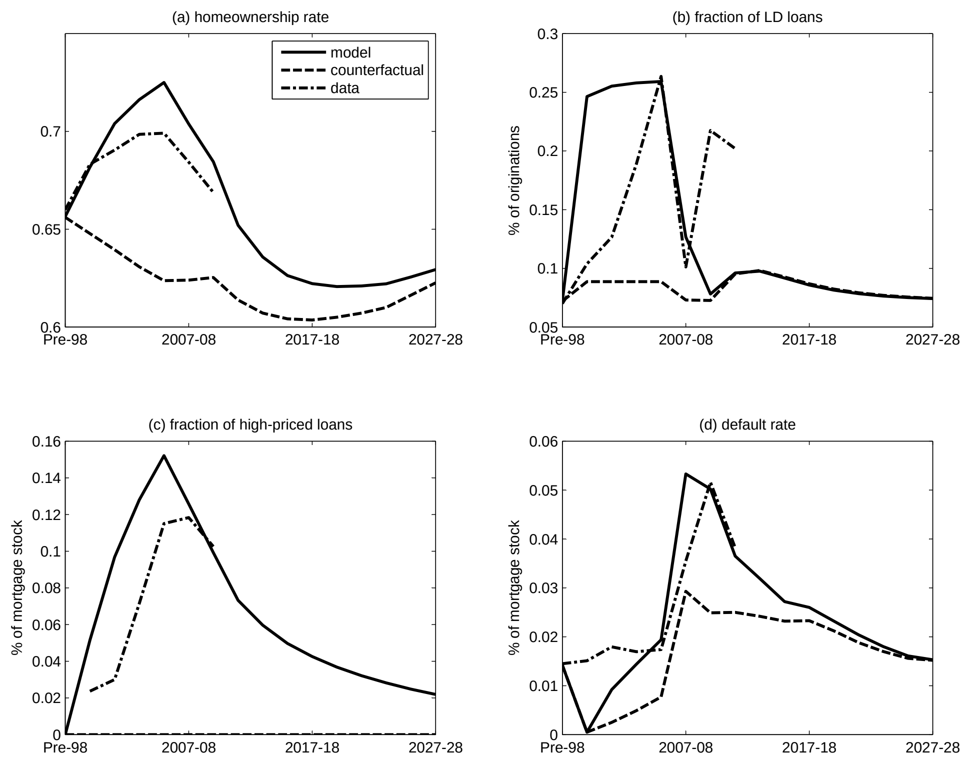


Figure 11: Low interest rates during the boom

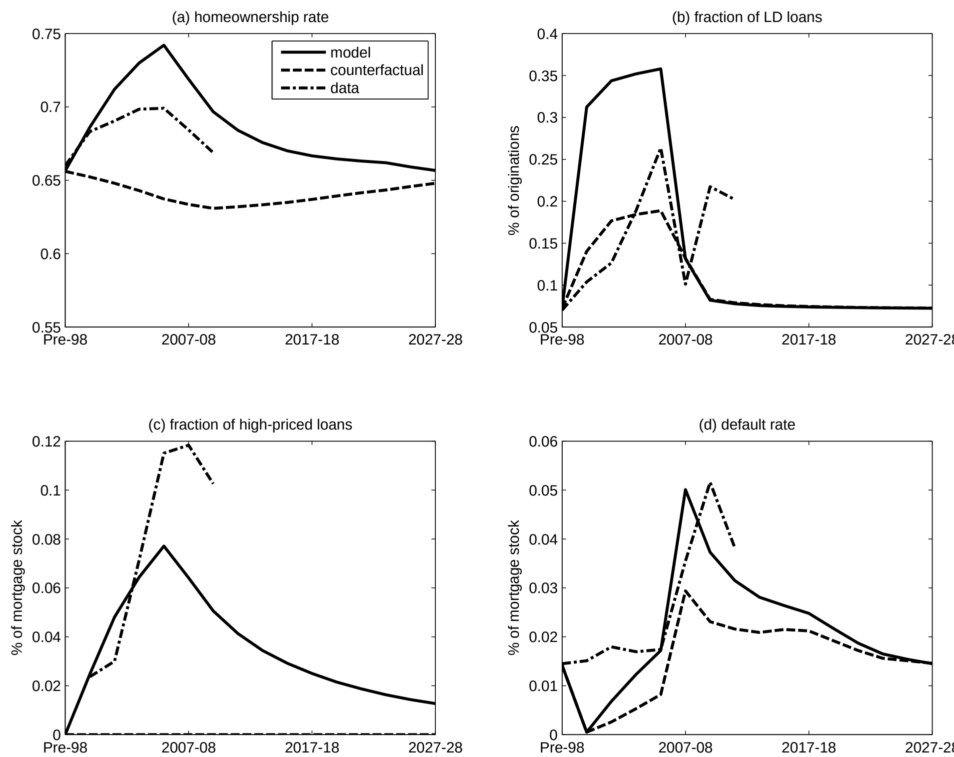


Figure 12: Broader recourse mitigates the crisis

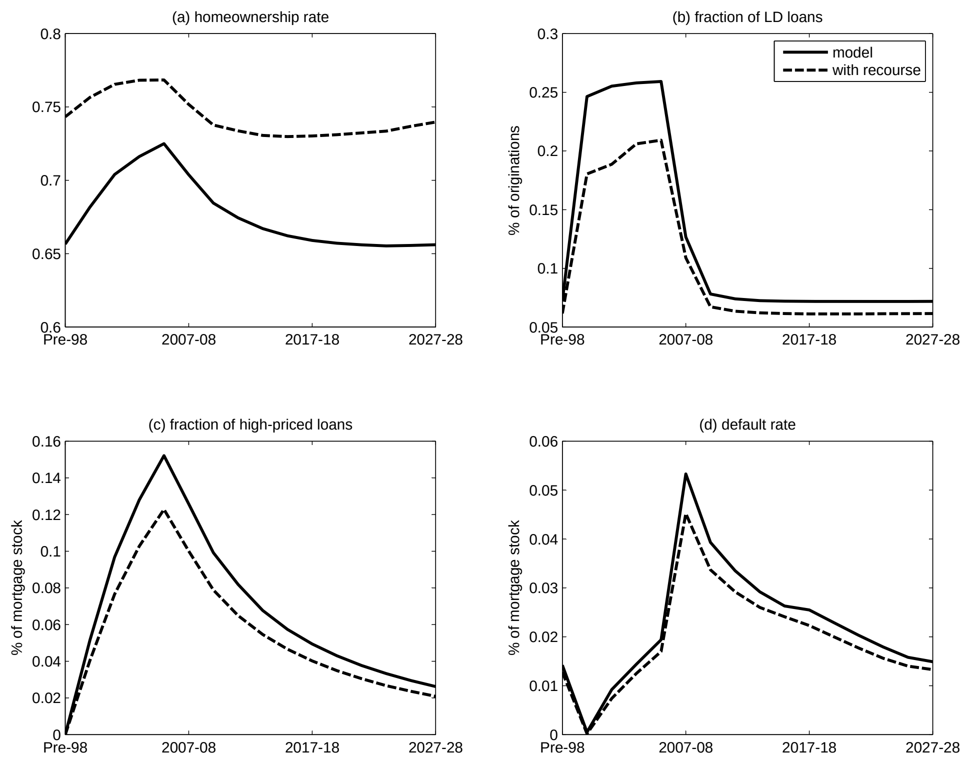


Figure 13: Alternative counterfactual