

Mortgage Debt, Consumption, and Illiquid Housing Markets in the Great Recession*

Carlos Garriga[†] Aaron Hedlund[‡]

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Abstract

Using a quantitative heterogeneous agents macro-housing model and detailed micro data, this paper studies the drivers of the 2006–2011 housing bust, its spillovers to consumption and the credit market, and the ability of mortgage rate interventions to accelerate the recovery. The model features tenure choice between owning and renting, rich portfolio choice, long-term defaultable mortgages, and endogenously illiquid housing from search frictions. The equilibrium analysis and empirical evidence suggest that the deterioration in house prices *and liquidity*—transmitted to consumption via balance sheets that vary in composition and depth—is central to explaining the observed aggregate and cross-sectional patterns.

Keywords: Housing; Consumption; Liquidity; Debt; Great Recession

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[†]Federal Reserve Bank of St. Louis. E-mail: carlos.garriga@stls.frb.org

[‡]University of Missouri, Federal Reserve Bank of St. Louis, and Center for Growth and Opportunity at Utah State University. E-mail: hedlunda@missouri.edu.

1 Introduction

The years since house prices reached their 2006 apex have witnessed the largest disruption in U.S. housing market and macroeconomic activity since the Great Depression. Between 2006 and 2011, house prices fell by over 25% in tandem with steep declines in income, employment, and consumption. At the same time, foreclosures reached record heights, and the evaporation of *housing liquidity* produced severe selling delays and mounting unsold inventories. With house prices now exceeding their previous peak, questions remain regarding the drivers of the housing bust, its channels of macroeconomic transmission, and the effects of crisis-related interventions. This paper establishes that the deterioration in housing liquidity, together with falling house prices, is central to explaining these patterns, both in the aggregate and cross section.

One of the main challenges for traditional macroeconomic models is their inability to generate sizable house price and consumption declines consistent with the data.¹ In response, this paper develops an equilibrium incomplete markets macro-housing model with several key features: tenure choice between renting and owning, portfolio choice between liquid assets, housing, and long-term defaultable mortgage debt, and a frictional housing market. Specifically, directed search in the housing market generates **endogenous liquidity** by creating a tension between trading at a desirable price—low for buyers, high for sellers—versus trading quickly. This liquidity responds to changing macroeconomic conditions, resulting in time-varying selling delays. In the mortgage market, credit liquidity also evolves over time as measured by the default premia priced into new loans by lenders at origination as they evaluate changes to foreclosure risk. The model is parametrized to match

¹See Davis and Van Nieuwerburgh (2015) and Piazzesi and Schneider (2016).

pre-crisis U.S. data, then subjected to a series of observed shocks and used to study the drivers of the housing bust along with its transmission to aggregate and cross-sectional consumption. The model is then used to evaluate mortgage rate interventions aimed at restoring the housing market and macroeconomy.

To summarize, higher left tail risk from earnings skewness shocks and tightening lending standards emerge as the main drivers of the housing crash in the model. Alternative explanations based on productivity disasters or unobserved shocks to housing preferences or beliefs fall short and give rise to other counterfactual model predictions. Going from housing to consumption, the deterioration in housing liquidity along with falling prices makes ownership riskier and damages household balance sheets. The imbalance that arises between assets and liabilities creates debt overhang that triggers rising selling delays and higher foreclosures, which in turn induces lenders to contract credit. The twin collapses in housing and credit liquidity generate substantial macroeconomic amplification and propagation, and they are also responsible for the severe decline in housing sales. Lastly, mortgage rate reductions boost house prices and accelerate the consumption recovery, mostly by repairing household balance sheets rather than through intertemporal substitution.

Digging deeper into the results, about half of the nearly 25% house price decline comes from earnings skewness shocks and almost a quarter from tighter credit limits. While the baseline analysis also includes negative productivity shocks and a temporary rise in the risk-free rate coinciding with the 2005–2007 tightening of monetary policy, each has only a modest impact. Besides driving much of the decline and slow recovery in house prices, skewness shocks are also essential to explain the fall in homeownership. Without them, the other shocks actually *increase* the ownership rate by pushing down prices and making homes more affordable. The distinguishing feature of worse earnings skewness is that

it increases downside uncertainty, which makes the consumption commitment of owning an illiquid house and its associated burden of mortgage payments particularly unattractive. Tighter credit limits play a major role by restricting funding both to new buyers and owners looking to extract equity, which has the perverse effect of *exacerbating* debt overhang by giving distressed owners no other consumption smoothing options besides attempting to sell or defaulting.

The combined effect of endogenously deteriorating housing liquidity and falling house prices more than quadruples the spike in foreclosures compared to a version of the model with exogenous housing liquidity via fixed transaction costs. With exogenous liquidity, default is driven by a combination of negative equity and bad income shocks, i.e. the standard *double trigger* hypothesis. By contrast, the baseline gives rise to a **liquidity-adjusted double trigger** that weakens the negative equity requirement and expands the default region to include a segment of borrowers who have equity on paper but fail to sell because of trading delays, thus amplifying foreclosure activity. The data provides empirical support for the liquidity-adjusted double trigger, with each additional month of county-level average time on the market being associated with a 0.81 percentage point rise in mortgage default.

To make matters worse, lenders respond by pricing higher premia into new mortgages, which sets off a downward spiral of deteriorating housing and credit liquidity that amplifies the fall in house prices and consumption in the model by 26% and 34%, respectively. In the data, each 30-day rise in county-level time on the market is associated with more than a \$900 income drop after controlling for the decline in house prices. This negative effect of deteriorating housing liquidity on the ability to sell and on the availability of credit also provides the missing piece to resolving the puzzle of positively co-moving prices and sales in the data, whereas Walrasian models tend to produce counterfactual spikes

in sales as low prices drive buyers into the market to purchase cheap homes.

Deteriorating housing conditions spill over to the rest of the economy, with an aggregate elasticity of consumption to house prices in the model of 0.17 and an empirical elasticity of 0.20 using income as a proxy at the county level. Importantly, these spillovers to consumption through the household balance sheet are persistent in the presence of endogenous housing liquidity, whereas they dissipate rapidly without selling delays. A richer cross-sectional analysis reveals the importance of **balance sheet depth**, which refers to the composition of household portfolios into gross positions rather than the more conventional approach of just summarizing balance sheets by net worth. When reductions in house prices create an imbalance between assets and liabilities, households possessing deeper and more illiquid balance sheets—that is, larger gross positions in the form of bigger houses and bigger mortgages—experience sharper consumption declines than households with balance sheets that are similar in net worth but shallower and more liquid. This is especially true when comparing renters and highly leveraged owners with similar net worth because of low equity. Both in the model and data, renters experience only modest consumption declines during the crisis, whereas indebted owners suffer a *three times larger* drop as their wealth becomes more difficult to adjust.

Finally, this paper finds that mortgage rate reductions are a potent policy tool that accelerates the recovery in house prices and consumption by 47% and 30%, respectively. Cheaper borrowing is directly responsible for the rise in prices, and it is this equilibrium price response that explains most of the increase in consumption, rather than direct cash-flow effects or intertemporal substitution. In particular, higher house prices repair household balance sheets by alleviating debt overhang—especially for highly leveraged owners, whose consumption response is three times larger than that of less indebted owners.

Related Literature Davis and Van Nieuwerburgh (2015) and Piazzesi and Schneider (2016) summarize an extensive literature on housing and the macroeconomy, much of which has historically focused on higher-frequency house price movements. However, in recent years, some of this attention has shifted away from the business cycle to explaining large housing market swings.

One strand of the literature uses search models to study fluctuations in liquidity as a source of housing market variation, including Wheaton (1990), Piazzesi and Schneider (2009), Caplin and Leahy (2011), Díaz and Jerez (2013), Ngai and Tenreyro (2014), Head, Lloyd-Ellis and Sun (2014), and Piazzesi, Schneider and Stroebel (2019). However, these search models preclude borrowing and saving, leaving no role for credit to impact housing. Hedlund (2016a,b) are exceptions, but this paper is the first to study the interaction of credit and liquidity during crisis episodes.

The importance of credit for house price dynamics has been emphasized by Landvoigt, Piazzesi and Schneider (2015), Justiniano, Primiceri and Tambalotti (2015), Favilukis, Ludvigson and Van Nieuwerburgh (2017), and Garriga, Manuelli and Peralta-Alva (2019). This paper finds credit to be a driver of the crisis but also emphasizes the role of downside earnings risk from skewness shocks. Stock and Watson (2012), Guvenen, Ozkan and Song (2014), and Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry (2018) also establish the macroeconomic significance of higher order moment shocks.

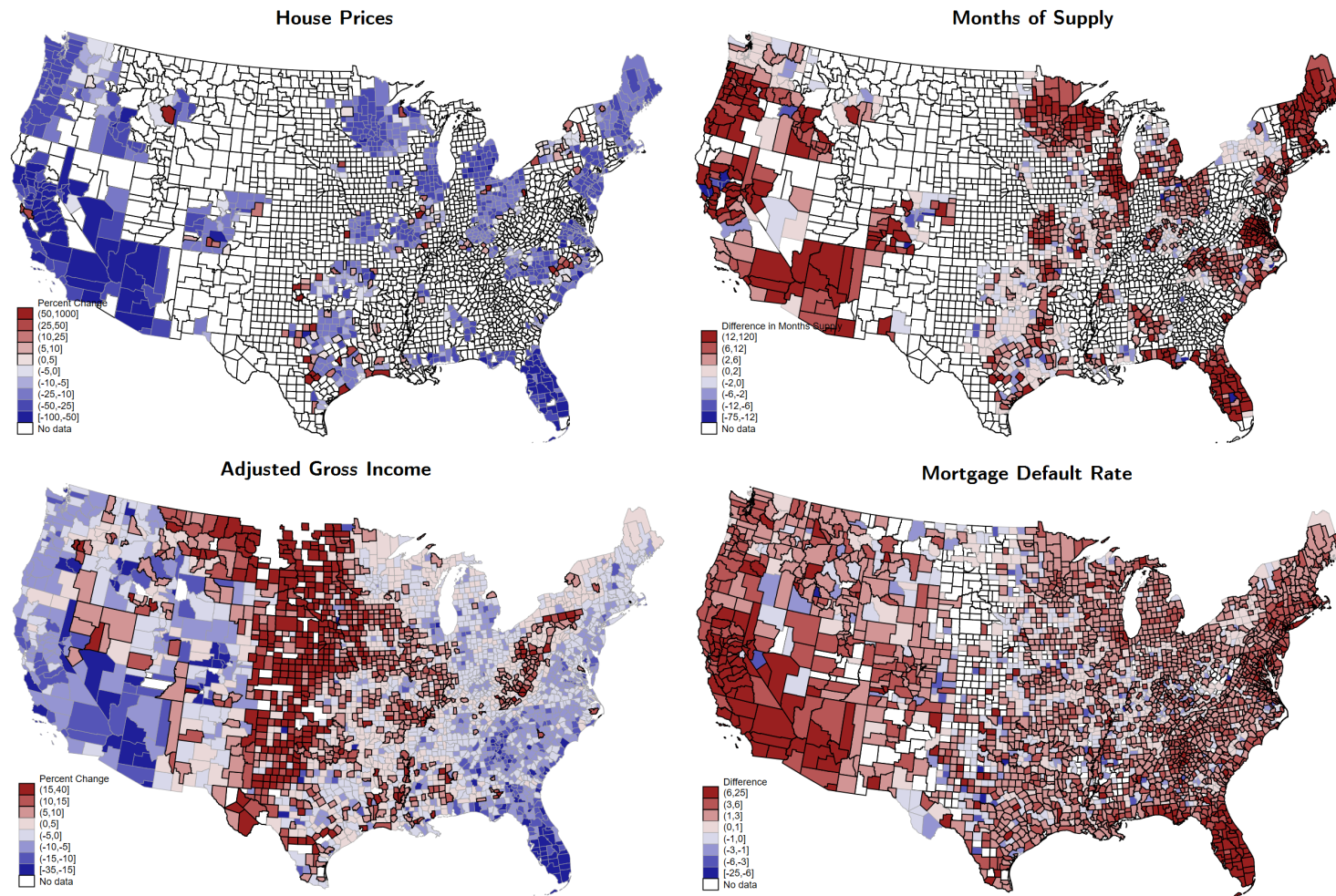
Several papers also study the transmission from housing to consumption, such as Mian, Rao and Sufi (2013), Berger, Guerrieri, Lorenzoni and Vavra (2018), and Kaplan, Mitman and Violante (2019). This paper contributes to the literature by producing quantitative and empirical evidence regarding the importance of endogenous housing liquidity and balance sheet depth for the response of aggregate and cross-sectional consumption.

2 Data Sources

This paper utilizes several sources of rich, micro-level data. On the housing side, CoreLogic provides MLS listing-level data for much of the United States, with coverage increasing over time. From peak to trough, inflation-adjusted average closing prices fell by over 36% in the MLS, which is somewhat greater than the drop in prices reported by the Federal Housing Finance Agency (FHFA) and Case-Shiller in appendix figure 9. The MLS data also show that months of supply—which is a measure of housing illiquidity equal to the ratio of houses on the market to monthly sales—jumped by over 10 months during the crisis. Besides the MLS, this paper uses loan-level Equifax data to track mortgage default—which rose by over 5 percentage points—and to assist in constructing a county-level measure of net worth for the regressions in section 5.2. The remaining data on zip-code level income and county-level employment are publicly available from the IRS Statistics of Income (SOI) and Bureau of Labor Statistics Quarterly Census of Employment and Wages (BLS QCEW), respectively. In addition, some of the regressions utilize industry employment data from the Census County Business Patterns (CBP). Appendix A provides additional details, and table 11 gives more complete summary statistics.

The county-level heat maps in figure 1 illustrate the geography of the crisis. Notably, the areas which experienced the worst deterioration in house prices and months of supply also suffered the largest rise in mortgage defaults and income declines.² The empirical analysis in section 5.2 confirms these patterns and establishes a strong connection between house price declines, drops in housing liquidity, and worse macroeconomic outcomes.

²According to figure 10 in the appendix, employment also falls in concert with house prices, consistent with Mian and Sufi (2014). Figures 11 and 12 show that average days on the market behaves similarly at the county level to months of supply.



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Figure 1: (Top Left) Percentage change in house prices, 2006 – 2011 (MLS). (Top Right) Change in months of supply, 2005 – 2008 (MLS). (Bottom Left) Percentage change in AGI, 2006 – 2011 (IRS). (Bottom Right) Change in the mortgage default rate, 2006 – 2010 (Equifax). Blue is a decline; red is an increase.

3 The Model

The model is a multi-sector open economy in discrete time with heterogeneous households, a frictional housing market, and defaultable long-term mortgages.

3.1 Households

Infinitely-lived households have preferences $u(c_t, c_{ht})$ over consumption c_t and housing services c_{ht} , which they obtain either as apartment renters or homeowners. Renters receive housing services $c_{ht} = a_t$ from apartment space $a_t \leq \bar{a}$ that is contracted on a spot market each period at unit cost r_{at} . Homeowners, by contrast, receive a continual stream of housing services $c_{ht} = h$ from their durable house $h_t \in H$ purchased in the decentralized housing market. To reflect the observed segmentation between the rental and owner-occupied markets, large dwellings are only available for purchase, i.e. $\bar{a} < \underline{h}$.³ Owners cannot have tenants or possess multiple houses simultaneously.⁴ Utility flows are discounted at the rate $\beta \in (0, 1)$.

Households supply one unit of raw labor with stochastic individual productivity $e_t \cdot z_t$ to the labor market, where z_t follows a finite-state Markov chain $\pi_z(z_{t+1}|z_t)$, and the transitory shock $e_t \in E \subset \mathbb{R}_+$ is drawn from $F(e)$.

3.2 Production

Goods firms operate a linear technology $Y_{ct} = Z_t N_{ct}$ that employs labor N_{ct} to produce the numeraire, which is used for consumption, financial market

³This assumption is consistent with empirical analyses of the rental and owner-occupied markets that find little evidence of arbitrage (Glaesar and Gyourko (2007)), distinct property characteristics (Halket, Nesheim and Oswald (2017)), and tenure status flows that indicate a strong degree of segmentation (Bachmann and Cooper (2014)). The gap between \bar{a} and \underline{h} captures the discrete jump in dwelling size that typically occurs during rent-own transitions.

⁴Own-to-own transitions occur when an owner sells and then buys in the same period.

trades, the production of apartment space at rate A (which implies $r_a = 1/A$), and the construction of new houses.⁵ Construction firms build houses with land/permits $\bar{L} > 0$ supplied by the government, structures S_{ht} from the goods sector, and labor N_{ht} using a constant returns to scale technology $Y_{ht} = F_h(\bar{L}, S_{ht}, N_{ht})$.⁶ Houses depreciate stochastically with probability δ_h , and there are no construction delays.⁷ Thus, the end of period housing stock follows $H_t = (1 - \delta_h)H_{t-1} + Y_{ht}$.

3.3 Housing Market

Heterogeneous home buyers and sellers direct their search by price and house size in a frictional, decentralized market where the risk of failing to transact creates endogenous **housing illiquidity**. In equilibrium, sellers face a negative trade-off between their choice of list price p_t^{list} and the probability η_{st} of selling, whereas buyers can increase their success rate η_{bt} by raising their bid price p_t^{bid} . For tractability, all housing trades are intermediated by real estate brokers.⁸ Specifically, owners sell to brokers, buyers purchase from brokers, and the brokers themselves—who also obtain housing from the construction sector and can trade with each other at price $p_t(h) = p_t h$ —act as passive market makers that equate the total flow of housing from sellers to buyers.⁹

⁵Sommer, Sullivan and Verbrugge (2013) and Davis, Lehnert and Martin (2008) report that real rents have remained mostly flat over the past 30 years relative to price swings.

⁶The government consumes the revenues from selling land/permits.

⁷Stochastic depreciation is needed to ensure a stationary housing stock with construction.

⁸Without brokers, direct matching between heterogeneous sellers and buyers creates a challenging multidimensional dynamic sorting problem where each side must forecast the dynamics of the entire distribution of income, assets, housing wealth, and debt in order to calculate their chances of trading in each submarket. Introducing brokers enhances tractability by dividing the single matching problem with two-sided heterogeneity into two matching problems that each have only one-sided heterogeneity.

⁹Brokers do not engage in strategic trading or speculative behavior, as they are not permitted to accumulate a stock of housing from one period to the next. Although brokers trade discrete houses $h \in H$ with buyers and sellers, the linearity of $p_t(h) = p_t h$ implicitly

3.3.1 Search in the Housing Market

Formally, the probability η_{st} that a seller matches with a broker in submarket (p_t^{list}, h_t) and the corresponding probability $\alpha_{st} = \eta_{st}/\theta_{st}$ that a broker matches a seller depend on the ratio $\theta_{st}(p_t^{list}, h_t)$ of brokers to sellers, i.e. the market tightness. Analogously, the probabilities for buyers meeting brokers and vice-versa in submarket (p_t^{bid}, h_t) are given by η_{bt} and $\alpha_{bt} = \eta_{bt}/\theta_{bt}$, respectively. To prevent price “fishing” that leads to excessive time on the market, sellers incur a small utility cost ξ in the event of a failed listing.

Brokers pay an entry cost $\kappa_s h$ and receive net revenue $p_t h_t - p_t^{list}$ when they successful match with a seller. Similarly, brokers pay $\kappa_b h$ to search for buyers and receive $p_t^{bid} - p_t h_t$ in the event of a successful match. Free entry of brokers into each submarket, which guarantees that they do not make any profits, determines market tightnesses as follows:

$$\kappa_b h_t \geq \overbrace{\alpha_{bt}(\theta_{bt}(p_t^{bid}, h_t))}^{\text{prob of match}} \overbrace{(p_t^{bid} - p_t h_t)}^{\text{net revenue}} \quad (1)$$

$$\kappa_s h_t \geq \overbrace{\alpha_{st}(\theta_{st}(p_t^{list}, h_t))}^{\text{prob of match}} \overbrace{(p_t h_t - p_t^{list})}^{\text{net revenue}} \quad (2)$$

where the conditions hold with equality in active submarkets.

The combination of directed search and free entry of brokers guarantees that the menu of tightnesses only depends on the price index p_t , not directly on the evolving cross-sectional distribution Φ_t of income, liquid assets, housing wealth, and mortgage debt. Denote the time-varying tightnesses as $\theta_{st}(p_t^{list}, h_t) = \theta_s(p_t^{list}, h_t; p_t)$ and $\theta_{bt}(p_t^{bid}, h_t) = \theta_b(p_t^{bid}, h_t; p_t)$, where $p_t = p_t(\Phi_t)$ is determined in equilibrium to ensure that the amount of housing sold to

assumes that they can exchange divisible units of housing capital with each other. In general, the per-unit price could be allowed to vary with h to capture segmentation, i.e. $p_t(h) = p_{ht}h$. Section B.2.3 discusses this house size conversion in more detail.

brokers equals the quantity purchased by buyers. For simplicity, denote $\eta_t^{sell}(p_t^{list}, h) \equiv \eta^{sell}(p_t^{list}, h; p_t) \equiv \eta_s(\theta_s(p_t^{list}, h; p_t))$ and likewise for $\eta_t^{buy}(p_t^{bid}, h)$.

3.3.2 House Price Determinants

This model structure allows equilibrium house price dynamics to deviate from those implied by existing workhorse housing frameworks. It is useful to discuss which assumptions account for these differences in house price dynamics. First, although the construction technology is constant returns to scale, the fixed supply of new land permits each period results in an upward sloping supply of newly constructed houses.¹⁰ As a result, house prices are determined both by demand and supply conditions rather than just construction costs. Second, the segmentation between rental apartments and owner-occupied housing eliminates the possibility of arbitrage by preventing developers from converting apartment space into houses or vice-versa. This assumption effectively weakens the connection between rents and house prices that is present in user cost frameworks. Third, agents in the model are restricted to own at most one house at a time from a discrete set of house sizes, which prevents a rich, unconstrained marginal buyer from determining house prices. Lastly, search frictions impede agents' ability to respond quickly to current and future expected conditions.

3.4 Financial Markets

Households save using risk-free bonds which trade in open financial markets at an exogenous rate i_{t+1} . In addition, homeowners can borrow against their

¹⁰Even if construction were perfectly elastic, prices could fall below construction costs in a downturn because the housing stock is durable and cannot be transformed back into consumption through demolition.

house using long-term, fixed-rate mortgages that contain a default option.¹¹

3.4.1 Fixed-Rate Mortgages

A mortgage (\bar{r}, m_t) is defined by its balance m_t and the borrower's fixed rate \bar{r} , which was equated to the market rate $r_{\tau+1}$ in the origination period $\tau \leq t$. Thus, \bar{r} may differ from the *current* r_{t+1} if market rates have changed.

Origination Both for purchase loans and refinancing, mortgages are priced based on the state of the economy and each borrower's individual default risk *assessed at the time of origination*. Specifically, for a borrower with a house of size h , liquid assets b_{t+1} , and persistent income z_t who chooses loan size m_{t+1} , a competitive lender issues $q_t m_{t+1}$ units of the numeraire to the borrower, where the loan-specific mortgage price $q_t((\bar{r} \equiv r_{t+1}, m_{t+1}), b_{t+1}, h, z_t)$ is akin to paying upfront points. The price $q_t(\cdot)$ compensates the lender for the origination cost ζ , for the risk of borrower default, and for any interest rate risk created by deviations of future r_{t+1} from \bar{r} . Importantly, the pricing of all these risks only occurs at origination because of the long-term nature of mortgage contracts.

Repayment and Refinancing During repayment, the mortgage contract specifies a minimum interest-only payment, and beyond that, borrowers choose the pace of amortization. Thus, there is no prescribed loan duration.¹² Formally, borrowers choose a payment amount l_t in excess of the minimum $\bar{r}/(1 + \underline{r})m_t$ necessary to ensure a declining balance $m_{t+1} \equiv (m_t - l_t)(1 + \underline{r}) \leq$

¹¹Garriga and Hedlund (2018) explore the implications of fixed vs. adjustable rate mortgages. The presence of floating rates has important macroeconomic consequences.

¹²This arrangement stands in for the ability of borrowers to circumvent any rigid amortization schedule by using additional liens (e.g. second mortgages, home equity lines of credit) to adjust cumulative leverage. In addition, it economizes computation by eliminating the need to track remaining loan duration as a state variable.

m_t . Alternatively, they can choose to default, or they can repeat the costly origination process by refinancing into a new loan m_{t+1} to extract equity $m_{t+1} > m_t$ or lower their rate \bar{r} if the market rate r_{t+1} has fallen.

Default If a borrower chooses to default, lenders foreclose with probability φ , which results in immediate repossession of the house and complete debt forgiveness, but at a cost. In particular, borrowers face the consequence of a default flag, $f_t = 1$, that excludes them from participation in the mortgage market until the flag disappears with probability $1 - \gamma_f$. Lenders ignore the skipped payment with probability $1 - \varphi$, in which case the borrower stays in the house and carries balance m_t into the next period.

3.4.2 Mortgage Pricing

The market rate r_{t+1} for new mortgages tracks the long-horizon cost of external financing for lenders plus a premium.¹³ All other sources of risk to lenders enter the pricing function q_t , which forecasts borrower behavior and delivers zero ex-ante profits loan-by-loan from perfect competition.

¹³This premium compensates for mortgage servicing costs ϕ and the risk of stochastic house depreciation. In the low-probability event of a house depreciation, owners lose any accumulated equity but also have their debt forgiven without receiving a flag.

The price of loan (\bar{r}, m_{t+1}) for borrower (b_{t+1}, h, z_t) satisfies the recursion

$$(1 + \zeta)q_t((\bar{r}, m_{t+1}), b_{t+1}, h, z_t) = \frac{1}{1 + r_{t+1}} \mathbb{E} \left\{ \underbrace{\eta_{t+1}^{sell}}_{\text{sell, repay}} + \underbrace{(1 - \eta_{t+1}^{sell})}_{\text{no house sale}} \left[\underbrace{d_{t+1}^*}_{\text{default}} \varphi \overbrace{\min \left\{ 1, \frac{J_{t+1}^{REO}(h)}{m_{t+1}} \right\}}^{\text{foreclosure recovery ratio}} \right. \right. \\ \left. \left. + \underbrace{d_{t+1}^*(1 - \varphi)(1 + \zeta)q_{t+1}^{delinq}}_{\text{continuation value of delinquency}} + (1 - d_{t+1}^*) \left\{ \mathbf{1}_{[\text{Refi}, t+1]} + \mathbf{1}_{[\text{No Refi}, t+1]} \underbrace{\left(\frac{l_{t+1}^* + (1 + \zeta)q_{t+1}^{cont} m_{t+2}^*}{m_{t+1}} \right)}_{\text{payment + continuation value}} \right\} \right] \right\}$$

such that

$$\begin{aligned} \eta_{t+1}^{sell} &\equiv \eta_s(\theta_s(p_{t+1}^{list*}, h; p_{t+1})) \quad (\text{probability of house sale}) \\ q_{t+1}^{delinq} &\equiv q_{t+1}((\bar{r}, m_{t+1}), b_{t+2}^{delinq*}, h, z_{t+1}) \quad (\text{mark-to-market price for delinquent } m_{t+1}) \\ q_{t+1}^{cont} &\equiv q_{t+1}((\bar{r}, m_{t+2}^*), b_{t+2}^*, h, z_{t+1}) \quad (\text{mark-to-market price for updated } m_{t+2}^*) \\ m_{t+2}^* &= (m_{t+1} - l_{t+1}^*)(1 + \bar{r}) \quad (\text{endogenous amortization}) \end{aligned} \tag{3}$$

where the variables with asterisks represent the household policy functions in period $t + 1$, and $J_{t+1}^{REO}(h)$ is the lender's value of repossessing a type- h house.

In words, the entire mortgage is paid off if the owner terminates the loan by selling or refinancing. If the homeowner defaults (typically after attempting and failing to sell), the lender either forecloses and receives the recovery ratio or else marks-to-market the continuation value of the delinquent borrower's loan. Otherwise, if the borrower makes a regular principal and interest payment l_{t+1}^* , the lender marks-to-market the continuation value of the mortgage with updated loan balance m_{t+2}^* . Future housing illiquidity $1 - \eta_{t+1}^{sell}$ depresses mortgage prices—that is, credit liquidity—by increasing the probability of a failed listing that leads to default and by reducing the recovery ratio.

3.4.3 Foreclosure Sales and the Recovery Ratio

Lenders face the same trading frictions as other sellers when managing their real-estate-owned (REO) properties, except they also lose a fraction χ of proceeds upon selling to foreclosure costs. Unsold properties require the payment of maintenance and property taxes $\gamma p_t h$. The value J_t^{REO} of a repossessed property with an option value R_t^{REO} of selling is

$$J_t^{REO}(h) = R_t^{REO}(h) - \gamma p_t h + \frac{1 - \delta_h}{1 + i_{t+1}} J_{t+1}^{REO}(h)$$

$$R_t^{REO}(h) = \max \left\{ 0, \max_{p_t^{REO} \geq 0} \eta_t^{sell}(p_t^{REO}, h) \left[(1 - \chi) p_t^{REO} - \left(-\gamma p_t h + \frac{1 - \delta_h}{1 + i_{t+1}} J_{t+1}^{REO}(h) \right) \right] \right\} \quad (4)$$

where the time subscripts in the value functions indicate dependence on p_t , i_{t+1} , and $\theta_{st}(\cdot) \equiv \theta_s(\cdot; p_t)$. The law of motion for the beginning-of-period type- h REO stock $H_t^{REO}(h)$ is

$$H_{t+1}^{REO}(h) = (1 - \delta_h) [1 - \eta_t^{sell}(p_t^{REO}, h)] \left(H_t^{REO}(h) + \int d_t^* [1 - \eta_t^{sell}(p_t^{list*}, h)] d\Phi_t^{own}(\cdot; h) \right)$$

where d_t^* and p_t^{list*} are household choices, and Φ_t^{own} is the owner distribution.

3.5 Household Behavior

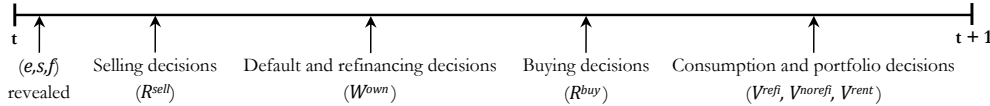


Figure 2: Decision-Making Timeline

Household decisions take place within the period in several stages given by the timeline in figure 2. An owner's state vector includes cash-at-hand y_t ,

mortgage rate \bar{r} and balance m_t , house h_t , shock z_t , and flag f_t . A renter's state is (y_t, z_t, f_t) . The exposition proceeds backwards, with $f_t \in \{0, 1\}$ written in the superscript and the time subscripts indicating the household problem's dependence on time-varying i_{t+1} , w_{t+1} , r_{t+1} , q_t , and p_t .

3.5.1 Consumption and Balance Sheet Decisions

Owners with no outstanding mortgage (including recent buyers and refinancing borrowers) pay for consumption c_t , maintenance and property taxes $\gamma p_t h$, and savings $b_{t+1}/(1 + i_{t+1})$ using cash-at-hand and new borrowing. They solve

$$V_t^{own,0}(y_t, h, z_t) = \max_{\substack{m_{t+1} \geq 0, \\ b_{t+1} \geq 0, \\ c_t \geq 0}} u(c_t, h) + \beta \mathbb{E} \left[\begin{array}{l} (1 - \delta_h)[W_{t+1}^{own,0}(y_{t+1}, (r_{t+1}, m_{t+1}), h, z_{t+1}) \\ + R_{t+1}^{sell,0}(y_{t+1}, (r_{t+1}, m_{t+1}), h, z_{t+1})] \\ + \delta_h[V_{t+1}^{rent,0}(y_{t+1}, z_{t+1}) + R_{t+1}^{buy,0}(y_{t+1}, z_{t+1})] \end{array} \right]$$

subject to

$$c_t + \gamma p_t h + b_{t+1}/(1 + i_{t+1}) \leq y_t + q_t((r_{t+1}, m_{t+1}), b_{t+1}, h, z_t)m_{t+1}$$

$$q_t((r_{t+1}, m_{t+1}), b_{t+1}, h, z_t)m_{t+1} \leq \vartheta p_t h$$

$$y_{t+1} = w_{t+1}e_{t+1}z_{t+1} + b_{t+1}$$

(5)

where ϑ is the collateral constraint at origination, $\bar{r} \equiv r_{t+1}$ is the fixed rate for the new loan, and $q_t(\cdot)$ reflects the current pricing of the borrower's default risk. Lastly, $W_{t+1}^{own,0}$ is the beginning-of-period value of owning that incorporates the decision to default, amortize, or refinance, $R_{t+1}^{sell,0}$ is the option value of selling, and their counterparts for owners who lose their homes in the unlikely event of stochastic depreciation are $V_{t+1}^{rent,0}$ and $R_{t+1}^{buy,0}$, respectively.

Homeowners who make an amortization payment l_t on their mortgage solve

$$V_t^{amort}(y_t, (\bar{r}, m_t), h, z_t) = \max_{\substack{b_{t+1} \geq 0, \\ c_t \geq 0, \\ l_t}} u(c_t, h) + \beta \mathbb{E} \left[\begin{array}{l} (1 - \delta_h)[W_{t+1}^{own,0}(y_{t+1}, (\bar{r}, m_{t+1}), h, z_{t+1}) \\ + R_{t+1}^{sell,0}(y_{t+1}, (\bar{r}, m_{t+1}), h, z_{t+1})] \\ + \delta_h[V_{t+1}^{rent,0}(y_{t+1}, z_{t+1}) + R_{t+1}^{buy,0}(y_{t+1}, z_{t+1})] \end{array} \right]$$

subject to

$$c_t + \gamma p_t h + b_{t+1}/(1 + i_{t+1}) + l_t \leq y_t$$

$$\frac{\bar{r}}{1 + \bar{r}} m_t \leq l_t \leq m_t$$

$$m_{t+1} = (m_t - l_t)(1 + \bar{r})$$

$$y_{t+1} = w_{t+1} e_{t+1} z_{t+1} + b_{t+1}$$
(6)

Owners with a default flag that prohibits them from borrowing have budget constraint $c_t + \gamma p_t h + b_{t+1}/(1 + i_{t+1}) \leq y_t$, while renters face the constraint $c_t + r_a a_t + b_{t+1}/(1 + i_{t+1}) \leq y_t$. Appendix C gives their optimization problems.

3.5.2 House Buying Decisions

Buyers choose (p_t^{bid}, h_t) and face the constraint $p_t^{bid} \leq y_t$ if they have a flag or $p_t^{bid} \leq y_t - \underline{y}(h_t, z_t)$ if they can borrow, where $\underline{y}(h_t, z_t) < 0$ is the endogenous borrowing limit at origination.¹⁴ The value function for buyers with credit is

$$R_t^{buy,0}(y_t, z_t) = \max\{0, \max_{\substack{h_t \in H, \\ p_t^{bid} \leq y_t - \underline{y}}} \eta_t^{buy}(p_t^{bid}, h_t)[V_t^{own,0}(y_t - p_t^{bid}, h_t, z_t) - V_t^{rent,0}(y_t, z_t)]\}$$
(7)

The value function for buyers without credit access is analogous.

¹⁴ $\underline{y}(h_t, z_t) = \min_{\substack{q_t m_{t+1} \leq \vartheta p_t h_t, \\ b_{t+1} \geq 0}} [b_{t+1}/(1 + i_{t+1}) - q_t((r_{t+1}, m_{t+1}), b_{t+1}, h_t, z_t)m_{t+1}]$

3.5.3 Mortgage Default, Amortization, and Refinancing Decisions

Homeowners with a mortgage decide whether to default, make an amortization payment, or refinance into a new loan. Their value function is

$$W_t^{own,0}(y_t, (\bar{r}, m_t), h, z_t) = \max \left\{ \varphi [V_t^{rent,1}(y_t, z_t) + R_t^{buy,1}(y_t, z_t)] \right. \\ \left. + (1 - \varphi) V_t^{delinq}(y_t, (\bar{r}, m_t), h, z_t), V_t^{amort}(y_t, (\bar{r}, m_t), h, z_t), V_t^{own,0}(y_t - m_t, h, z_t) \right\} \quad (8)$$

Borrowers who default lose their house but retain the immediate option to buy, albeit without access to credit. Borrowers who choose to refinance receive $V_t^{own,0}$ and enter the origination stage with updated cash-at-hand $y_t - m_t$ after paying off their existing loan. The delinquency value V_t^{delinq} is in the appendix.

3.5.4 House Selling Decisions

Indebted sellers must choose a list price $p_t^{list} \geq m_t - y_t$ sufficiently high to pay off their mortgage at the time of sale. Their option value of selling is

$$R_t^{sell,0}(y_t, (\bar{r}, m_t), h, z_t) = \max \{ 0, \max_{p_t^{list} \geq 0} \eta_t^{sell}(p_t^{list}, h) [V_t^{rent,0}(y_t + p_t^{list} - m_t, z_t) \\ + R_t^{buy,0}(y_t + p_t^{list} - m_t, z_t) - W_t^{own,0}(y_t, (\bar{r}, m_t), h, z_t)] + [1 - \eta_t^{sell}(p_t^{list}, h)] (-\xi) \}$$

subject to

$$p_t^{list} \geq m_t - y_t \quad (9)$$

where $R_t^{buy,0}$ is the option value of immediately searching for a new house. Debt overhang occurs when a binding constraint from high m_t causes long delays. Sellers without debt and those with default flags are unconstrained.

3.6 Equilibrium

A stationary equilibrium consists of value and policy functions for households and lenders; market tightness functions θ_s and θ_b ; prices w , i , r , q , p , and r_a ; and stationary distributions Φ of households and H_{REO} of REO houses such that agents optimize and the markets clear for housing and factor inputs. Appendix C provides all value functions and equilibrium conditions. The main quantitative experiments described in section 5 involve computing the dynamic equilibrium response of the model economy to some unanticipated shocks.

4 Parametrization

The model is parametrized to reproduce key features of the pre-crisis United States economy.¹⁵ Some parameters are identified from external sources, while the rest are set jointly to match moments related to the housing market and household portfolio holdings. The length of a time period is one quarter.

Households Following Storesletten, Telmer and Yaron (2004), the log of the persistent shock z_t follows an AR(1) process, and the transitory component e_t is log-normal.¹⁶ The Rouwenhorst method is used to discretize $\ln(z_t)$ into a 3-state Markov chain, and a fourth state is then added following Castañeda, Díaz-Giménez and Ríos-Rull (2003) to represent the top 1 percent of earners.

Households have CES utility with an intratemporal elasticity of

¹⁵This choice of starting point implicitly assumes that agents in the economy did not anticipate the subsequent unprecedented housing bust. Cheng, Raina and Xiong (2014) provide evidence for this assumption by showing that managers in securitized finance—who arguably were the most likely to be informed about real-time housing market conditions—did not engage in behavior that indicated they were anticipating a bust, such as timing the market or acting cautiously in their own home transactions. Gerardi, Lehnert, Sherlund and Willen (2008a) offer further support for the unanticipated nature of the housing bust.

¹⁶The appendix explains the procedure to convert the annual estimates to quarterly values.

substitution of $\nu = 0.13$, consistent with Flavin and Nakagawa (2008) and Kahn (2009). Risk aversion is set to $\sigma = 2$, while the consumption share ω and discount factor β are determined jointly.

Production The numeraire technology Z is set to normalize mean quarterly earnings to 0.25. Construction is Cobb-Douglas with a structures share of $\alpha_s = 0.3$ and land share of $\alpha_L = 0.33$ from the Lincoln Institute of Land Policy. The supply of new permits is normalized to $\bar{L} = 1$. Housing depreciates at an annualized rate of 1.4%, and A is set to generate an annualized rent-price ratio $r_a/p = (1/A)/p$ of 3.5%, consistent with Sommer et al. (2013).

Housing Market Matching is Cobb Douglas, giving trade probabilities of $\eta_s(\theta_s) = \min\{\theta^{\gamma_s}, 1\}$ and $\eta_b(\theta_b) = \min\{\theta^{\gamma_b}, 1\}$. Solving for θ_s and θ_b from equations (1) – (2) gives $\eta^{sell}(\cdot) \equiv \eta_s(\theta_s(\cdot; p))$ and $\eta^{buy}(\cdot) \equiv \eta_b(\theta_b(\cdot; p))$ as

$$\eta^{sell}(\cdot) = \min \left\{ 1, \max \left\{ 0, \left(\frac{ph - p^{list}}{\kappa_s h} \right)^{\frac{\gamma_s}{1 - \gamma_s}} \right\} \right\}, \quad \eta^{buy}(\cdot) = \min \left\{ 1, \max \left\{ 0, \left(\frac{p^{bid} - ph}{\kappa_b h} \right)^{\frac{\gamma_b}{1 - \gamma_b}} \right\} \right\}$$

The parameter $\gamma = 0.007$ reflects 2.8% annual property taxes and maintenance, while κ_b , κ_s , γ_s , γ_b , and the search disutility ξ are determined jointly.

Financial Markets To match values in the U.S. during 2003 – 2005, the *real* risk-free rate is set to -1% , and the origination cost is 0.4%. The servicing cost ϕ is set to equate the real mortgage rate to 3.6%. Lastly, a non-binding LTV limit of $\vartheta = 1.25$ (125%) is used.¹⁷ The persistence of credit flags is $\gamma_f = 0.95$, and the REO discount χ is determined in the joint calibration.

¹⁷See Herkenhoff and Ohanian (2019) for discussion of cash-out refinancing in the 2000s.

Table 1: Model Parametrization

Description	Parameter	Value	Target	Model	Source/Reason
External Parameters					
Autocorrelation	ρ	0.952			Storesletten et al. (2004)
SD of Persistent Shock	σ_ϵ	0.17			Storesletten et al. (2004)
SD of Transitory Shock	σ_e	0.49			Storesletten et al. (2004)
Transition to Top 1%*	$\pi_{3,4}$	0.0041			Kuhn and Ríos-Rull (2013)
Persistence of Top 1%*	$\pi_{4,4}$	0.9			Kuhn and Ríos-Rull (2013)
Intratemp. Elas. of Subst.	ν	0.13			Flavin and Nakagawa (2008)
Risk Aversion	σ	2			Standard Value
Structures Share	α_S	30%			Favilukis et al. (2017)
Land Share	α_L	33%			Lincoln Inst Land Policy
Taxes/Maintenance (Annual)	γ	2.8%			Moody's
Depreciation (Annual)	δ_h	1.4%			BEA
Rent-Price Ratio (Annual)	r_a	3.5%			Sommer et al. (2013)
Risk-Free Rate (Annual)	r	-1.0%			Federal Reserve Board
Servicing Cost (Annual)	ϕ	3.6%			3.6% Real Mortgage Rate
Mortgage Origination Cost	ζ	0.4%			FHFA
Maximum LTV	ϑ	125%			Fannie Mae
Prob. of Repossession	φ	0.5			2008 OCC Mortgage Metrics
Credit Flag Persistence	λ_f	0.9500			Fannie Mae
Jointly Determined Parameters					
Homeownership Rate	\bar{a}	2.7100	69.2%	69.2%	Census
Starter House Value	h_1	3.2840	2.75	2.75	Corbae and Quintin (2015)
Mean Net Worth**	z_4/z_3	5.500	2.83	2.84	2007 SCF
Housing Wealth (Owners)	ω	0.8159	3.97	3.97	2007 SCF
Borrowers with $LTV \geq 90\%$	β	0.9737	10.8%	10.7%	2007 SCF
Months of Supply***	ξ	0.0013	4.90	4.89	Nat'l Assoc of Realtors
Avg. Buyer Search (Weeks)	γ_b	0.0940	10.00	9.98	Nat'l Assoc of Realtors
Maximum Bid Premium	κ_b	0.0209	2.5%	2.5%	Gruber and Martin (2003)
Maximum List Discount	κ_s	0.1256	15%	15%	RealtyTrac
Foreclosure Discount	χ	0.1370	20%	20%	Pennington-Cross (2006)
Foreclosure Starts (Annual)	γ_s	0.6550	1.50%	1.25%	MBAA Delinquency Survey
Model Fit					
Borrowers with $LTV \geq 80\%$			20.6%	26.5%	2007 SCF
Borrowers with $LTV \geq 95\%$			6.7%	6.0%	2007 SCF
Mean Owner Liquid Assets			1.19	1.53	2007 SCF
Median Owner Liquid Assets			0.23	0.27	2007 SCF

*The transitions resemble table 20 from Kuhn and Ríos-Rull (2013) but have been adjusted to ensure that 1% of households have $z = z_4$. Furthermore, $\pi_{i,4} = 0$ and $\pi_{4,i} = 0$ for $i = 1, 2$.

**Net worth in the 2007 SCF is calculated as financial assets (excluding illiquid retirement savings) plus housing wealth minus outstanding mortgage debt.

***Months of supply, which is a housing liquidity measure that closely tracks average time on the market, is calculated as inventories divided by the sales rate.

Joint Parametrization The endogenously determined parameters are calculated to match moments from the data. The first set of moments targets select household portfolio statistics from the 2007 Survey of Consumer Finances (SCF). Specifically, the aim is to match average net worth, housing wealth, and the distribution of leverage, especially at the higher end, given that these households are the most vulnerable to a housing crash.¹⁸ Additional moments target key housing market variables such as average search duration, months of supply, maximum price spreads, pre-crisis foreclosure starts, and the average foreclosure discount. Table 1 provides a summary, and figure 14 in the appendix shows leverage in the model and the data.

5 Results

This section establishes the drivers of the housing bust, quantifies its aggregate and cross-sectional consequences, and assesses the effect of mortgage rate interventions on the recovery. The model suggests that earnings skewness and credit limits play a leading role in generating the crisis. Quantitative and empirical evidence demonstrate the importance of deteriorating housing liquidity and balance sheet depth as sources of amplification and transmission.

5.1 Drivers of the Crisis

The model is subjected to a joint series of observed shocks to productivity, interest rates, earnings skewness, and credit limits at new mortgage origination. The shocks all come as a surprise, but agents in the economy fully anticipate their duration and the response of all endogenous variables.¹⁹

¹⁸The SCF figures only include households in the bottom 99% of earnings *and* net worth.

¹⁹Because the shocks are not backed out, this exercise also serves as model validation.

Table 2: The Housing Market Collapse (Peak-Trough 2006–2011)

	Δ House Prices	Δ Ownership	Δ Months Supply	Δ Foreclosures
Model	−23.4%	−2.8pp	+6.5 months	+5.1pp
Data	−25.7%	−3.6pp	+6.0 months	+4.2pp

Sources: (House Prices) FHFA purchase index deflated by the PCE. (Foreclosures) Mortgage Bankers Association. (Months of Supply) National Association of Realtors. (Ownership) Census Bureau. pp = percentage point

5.1.1 Implementation and Model Fit

Evidence summarized by [Davis and Van Nieuwerburgh \(2015\)](#) points to fluctuations in income and interest rates as the primary drivers of house prices at the business cycle frequency. This fact, combined with declining productivity documented by [Fernald \(2014\)](#) and the tightening of monetary policy between 2005 and 2007, makes them a natural starting point for investigating the crisis. The model implementation for productivity consists of an unexpected 5% decline in Z_t in the goods sector that reverts after three years. For interest rates, the model is shocked with a four percentage point rise in i_t that lasts for two years, consistent with the data in figure 15.²⁰

Motivated by an extensive body of recent empirical literature, the model is also subjected to a credit supply shock and a rise in left tail earnings risk.²¹

²⁰Figure 15 also shows that mortgage rates r_t do *not* track i_t upward. Instead, lenders in the model price the short-lived rise in funding costs into upfront mortgage prices $q_t(\cdot)$, consistent with FHFA Mortgage Interest Rate Survey evidence on origination costs.

²¹[Gerardi, Lehnert, Sherlund and Willen \(2008b\)](#) and [Levitin and Wachter \(2015\)](#) document a rise from 2000 to 2006 in the use of secondary liens, or “piggyback loans,” with high cumulative loan-to-value (CLTV) ratios sometimes in excess of 100%. By 2006, this type of lending accounted for approximately 50% of originations and featured an average CLTV of 98.8%. However, [Lee, Mayer and Tracy \(2013\)](#) and [Avery, Bhutta, Brevoort, Canner and Gibbs \(2010\)](#) document that second lien originations dropped off precipitously from their mid-2006 market share of 24.3% to only 2.7% by 2008, and [Garriga \(2009\)](#) and [Driscoll, Kay and Vojtech \(2016\)](#) both report a large spike in loan denial rates. [Leventis \(2014\)](#) also shows a double-digit percentage point drop in the average CLTV for these loans between 2006 and 2009.

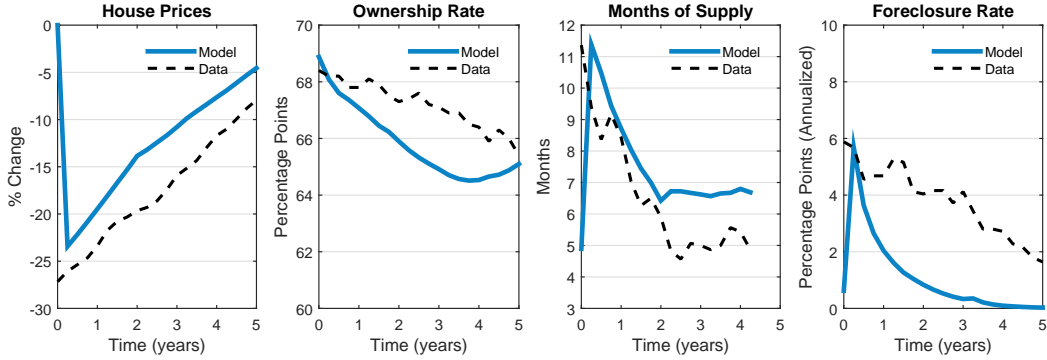


Figure 3: The housing recovery. Sources: (House Prices) FHFA purchase index deflated by the PCE. (Foreclosures) Mortgage Bankers Association. (Months of Supply) National Association of Realtors. (Ownership) Census.

The credit contraction in the model consists of a 90% maximum loan-to-value limit that applies at origination.²² To incorporate higher downside earnings risk, the individual process z_t is subjected to an unexpected skewness shock à la Guvenen, Karahan, Ozkan and Song (2019) which raises the probability that middle income households receive a bad persistent realization.²³ Importantly, the skewness shocks are constructed to replicate **only** the path of employment from the data in figure 15 and **not** any variables of interest.²⁴ The baseline implementation initiates all of the shocks simultaneously, but appendix

²²The tighter LTV constraint disappears after seven years, consistent with evidence in Davis, Larson and Oliner (2019) that shows a rebound in high-CLTV loans securitized by Fannie Mae. To simultaneously capture changes in lender foreclosure behavior during this same period, the probability of repossession φ in the model is lowered from 50% to 20%, and the probability of seeking a deficiency judgment increases from 0% to 50%. See Herkenhoff and Ohanian (2019) for additional discussion of changes in lender behavior during the crisis.

²³Recent empirical work has shown that earnings risk is countercyclical, asymmetric, and shows up as changes to earnings skewness. For example, Guvenen et al. (2014), Guvenen et al. (2019), and Salgado, Guvenen and Bloom (2017) present direct evidence of higher skewness leading into the Great Recession. Higher downside uncertainty as a partial cause of the Great Recession is also consistent with the deterioration in the University of Michigan Consumer Sentiment Survey, the NFIB Small Business Optimism Index, and the Company Reported Uncertainty Index from Handley and Li (2018) that began as early as 2006.

²⁴Specifically, the transition matrix π_z is replaced with new transitions $\tilde{\pi}_z^{recession}(z'|z)$. Details: $\tilde{\pi}_z^{recession}(z_2|z) = (1 - 0.026)\pi_z(z_2|z)$ for all z , $\tilde{\pi}_z^{recession}(z_j|z) = \pi_z(z_j|z)$ for all z and $j = 2, 3$, and $\tilde{\pi}_z^{recession}(z_1|z)$ is increased until $\sum_{z'} \tilde{\pi}_z^{recession}(z'|z) = 1$ for all z .

Table 3: Consumption during the Housing Bust

	Aggregate	Renters	Owners	Low LTV	High LTV
Model	-9.9%	-3.9%	-11.2%	-5.7%	-15.2%
Data	-9.4%	-1.9%	-10.9%	-5.4%	-14.5%

Sources: (Disaggregated) PSID using the sample selection criteria of [Arellano, Blundell and Bonhomme \(2017\)](#). Low loan-to-value (LTV) is below 0.3, and high LTV is above 0.8. (Aggregate) NIPA nondurable consumption deflated by the PCE (detrended from extrapolated 1991 – 2000 linear trend).

section [B.4.1](#) shows that staggering the timing by delaying the skewness and productivity shocks leads to similar results.

The productivity and interest rate shocks alone are insufficient to replicate the observed housing crash. The productivity shock by itself only generates a 1.9% decline in house prices and 1.0% drop in consumption, while the interest rate hike in isolation only depresses house prices and consumption by 3.7% and 2.0%, respectively. However, together with skewness shocks and tighter credit, the model economy closely mimics the severity of the housing crisis reflected in table 2 as well as its slow recovery shown by figure 3. In particular, the model mirrors the approximate 25% decline in house prices, the persistent erosion of homeownership, and the evaporation of housing liquidity marked by the surge in months of supply.²⁵ The drop in prices and liquidity both contribute to a significant rise in the foreclosure rate, which section [5.2.1](#) discusses in detail.²⁶

Looking beyond housing, table 3 shows that aggregate consumption falls by nearly 10%, but this number obscures significant heterogeneity by tenure status and pre-crisis leverage. Whereas renters cut consumption by less than

²⁵The model also captures the hump-shaped pattern of inventories, which initially rise as unsold houses accumulate on the market before eventually being sold off.

²⁶Section [B.2](#) in the appendix shows that the cross-sectional behavior of foreclosures in the model is consistent with recent evidence showing that mortgage default during the crisis was widespread and not just confined to low-income households.

Table 4: The Role of Shocks to Earnings Skewness and Credit

	Baseline	Exclude*	Alone**	Impact Bounds
<i>Skewness Shock</i>				
Δ House Prices	-23.4%	-14.8%	-11.6%	[-11.6%, -8.6%]
Δ Ownership	-2.8pp	+1.2pp	-3.1pp	[-4.0pp, -3.1pp]
Δ Months Supply	+6.5m	+3.0m	+1.3m	[+1.3m, +3.5m]
Δ Foreclosures	+5.1pp	+1.1pp	+0.2pp	[+0.2pp, +4.0pp]
Δ Consumption	-9.9%	-6.3%	-2.8%	[-3.6%, -2.8%]
<i>Credit Shock</i>				
Δ House Prices	-23.4%	-19.1%	-5.6%	[-5.6%, -4.3%]
Δ Ownership	-2.8pp	-3.0pp	+0.9pp	[+0.2pp, +0.9pp]
Δ Months Supply	+6.5m	+3.5m	+0.3m	[+0.3m, +3.0m]
Δ Foreclosures	+5.1pp	+2.3pp	-0.2pp	[-0.2pp, +2.8pp]
Δ Consumption	-9.9%	-7.0%	-2.2%	[-2.9%, -2.2%]

*The shock's effect in this case is the difference between the "baseline" and "exclude" columns. **The other shocks are removed. See appendix table 15 for a more complete decomposition.

5%, highly leveraged owners—who may have similar net worth but deeper and more illiquid balance sheets—experience a drop of nearly 15%. In addition, the consumption decline is non-monotonic in net worth, owing in large part to differences in household portfolio composition.²⁷ Section 5.3 discusses these balance sheet issues in greater detail.

5.1.2 Understanding the Mechanics of Skewness and Credit Shocks

The impact of each shock is quantified by undertaking two decompositions. The "alone" column in table 4 measures each shock's effect in isolation, while the "exclude" column measures its marginal contribution by removing it while leaving the other shocks in place. The final column reports bounds.²⁸

²⁷See panel 2 of figure 17 in the appendix.

²⁸Table 15 and figure 22 in the appendix provide a full decomposition.

Skewness shocks significantly impact the housing market, with important spillovers to foreclosures and consumption. A few points merit special emphasis. First, the bounds on months of supply and foreclosures are much wider than for other variables, primarily because foreclosure behavior is highly *nonlinear* and depends on a confluence of income shocks, declining house prices, and evaporating housing liquidity from debt overhang, as section 5.2.1 discusses more thoroughly. Secondly, even though earnings *realizations* react only gradually to skewness shocks, consumption and house prices exhibit an immediate response because of precautionary behavior. Faced with greater downside risk, financially distressed owners rush to put their houses on the market, which causes prices to decline and selling delays to build. The outsized impact of skewness on distressed owners can be seen in appendix figure 24.²⁹

This reduced appetite for housing explains the third important point about skewness shocks, which is that they are the keystone ingredient for explaining the homeownership decline. In fact, all of the other shocks both individually and together actually *increase* homeownership by reducing house prices and improving affordability. What distinguishes skewness from the rest is how it affects the riskiness of owning as compared to renting. Rather than take on the burden of mortgage payments for an illiquid asset during times of elevated risk, households prefer to forgo this consumption commitment and rent instead.

Credit shocks also have a noticeable impact on the housing market. At the upper bound, they reduce consumption and house prices by nearly

²⁹Appendix figure 23 decomposes the effect of skewness shocks into earnings realizations vs. higher downside uncertainty. To isolate the effects of the shock realizations, the model is simulated under the assumption that agents are unaware of the skewness shocks and incorrectly believe their individual labor process has not changed. In the second scenario, the skewness shocks are removed but agents falsely believe otherwise. Consistent with recent work by Berger, Dew-Becker and Giglio (2019), the realizations are the most important factor, but uncertainty noticeably amplifies the response of foreclosures and consumption.

3% and 6%, respectively. Moreover, in conjunction with the other shocks, the tightening of credit activates the nonlinearities discussed previously and causes a substantial increase in foreclosures and months of supply. Intuitively, the inability to extract equity through refinancing forces many distressed homeowners to put their houses on the market, suffer long selling delays because of their small equity cushions, and in many cases default.³⁰

5.1.3 Alternative Explanations of the Housing Crisis

At times, discussion has divided along credit shocks versus beliefs as the primary impetus of the housing crisis.³¹ Although the previous section affirms the importance of credit, this paper makes the novel case that skewness shocks have an equally potent impact and are critical to explaining the ownership decline. For robustness, appendix section B.4 assesses the viability of some alternative drivers, notably shocks to housing preferences or beliefs. Each of them succeeds on some margins, but the common thread is that none of them improves upon the fit from section 5.1.1 or matches the large ownership decline. Often, they even *boost* ownership and miss along other dimensions.

5.2 The Importance of Housing Liquidity

To assess the importance of endogenous housing liquidity, search frictions are shut down and replaced with a fixed 6% transaction cost (e.g. realtor fees) that does not respond to housing market or macroeconomic conditions.³²

³⁰Importantly, there is no forced deleveraging, because the constraint only applies at origination. Thus, the outstanding stock of mortgage debt declines only modestly and gradually, primarily from reduced inflows because of declining homeownership rather than from a surge in outflows, which is consistent with evidence from Bhutta (2015).

³¹Cox and Ludvigson (2018) develop an empirical framework to discuss this dichotomy.

³²Díaz and Luengo-Prado (2010), Bajari, Chan, Krueger and Miller (2013), Iacoviello and Pavan (2013), Berger et al. (2018), and Berger and Vavra (2015) report similar values.

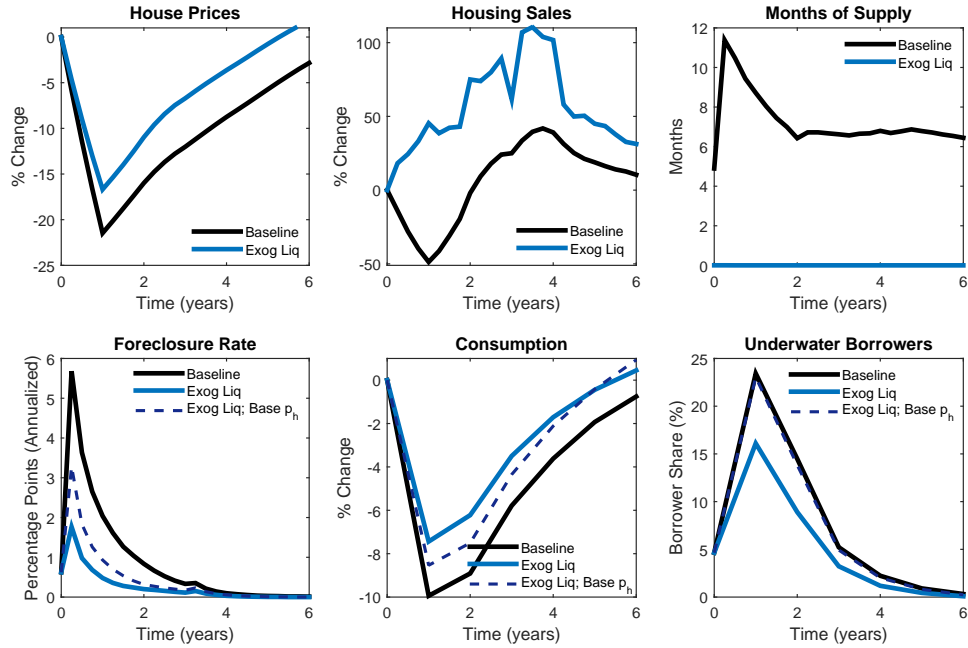


Figure 4: Baseline vs. exogenous liquidity. The dashed line shows the dynamics of the Walrasian economy when fed the price path from the baseline model.

Faced with the same shocks to productivity, interest rates, skewness, and credit constraints as before, the behavior of this Walrasian economy differs markedly from that of the baseline model. First, eliminating the endogenous liquidity response greatly attenuates the rise in foreclosures displayed in the bottom left panel of figure 4. Secondly, house prices and consumption fall by noticeably less in the Walrasian economy. Put another way, endogenous liquidity acts as a powerful amplification mechanism that deepens and prolongs the crisis. Lastly, by suppressing selling delays, the model with exogenous liquidity generates a counterfactual spike in sales during the crisis.³³ The

³³Even in an extreme scenario where realtor fees exogenously increase to 15% during the crisis, house prices only fall by 20.9% instead of 23.4%, leaving 19.2% of borrowers underwater compared to 23.4% in the baseline model and 23.1% in the data from CoreLogic (see <https://www.corelogic.com/downloadable-docs/corelogic-q4-2010-negative-equity-report.pdf>). Also, even with the spike in realtor fees, sales only fall by 15.7% compared to nearly 50% in the baseline and in the data.

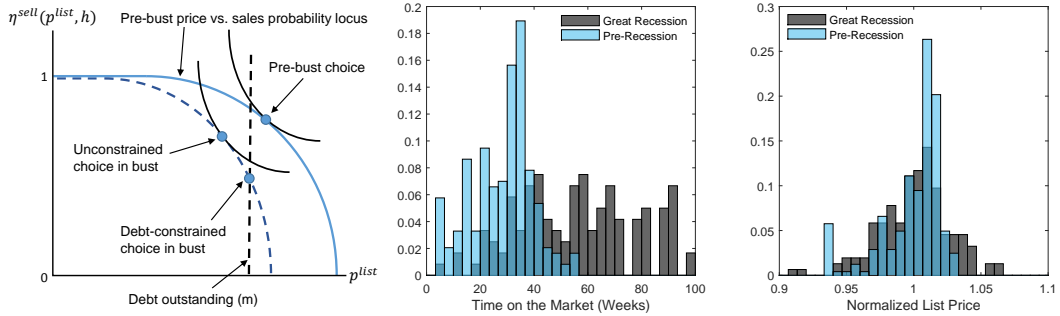


Figure 5: (Left) List prices and selling probabilities in booms and busts; dispersion of TOM (middle) and prices (right) before and during the crisis.

implications of endogenous liquidity for mortgage default, amplification, and sales behavior are discussed in sections 5.2.1, 5.2.2, and 5.2.3, respectively.

5.2.1 Default and the Liquidity-Adjusted Double Trigger

With endogenous liquidity, sellers face a trade-off between list price and time on the market that changes with economic conditions, as illustrated by the left panel of figure 5.³⁴ During good times, homeowners are able to sell quickly and at a high price. During bad times, the (p^{list}, η^{sell}) locus shifts inward and sellers prefer to adjust along *both margins* by accepting some increase in selling delays along with a lower price. However, the obligation to repay all mortgage debt at closing distorts list prices upward, which inflates time on the market. This **debt overhang** afflicts highly leveraged owners most severely and is responsible for the fatter right tail of the distributions of time on the market and prices during the Great Recession shown in figure 5.

The standard *double trigger* in the literature states that default requires a bad income shock and an inability to sell because of negative equity.³⁵ However, the model and data point to the overlooked importance of housing

³⁴Anenberg and Kung (2019) estimate a similar empirical trade-off.

³⁵See Campbell and Cocco (2015) and Gerardi, Herkenhoff, Ohanian and Willen (2018).

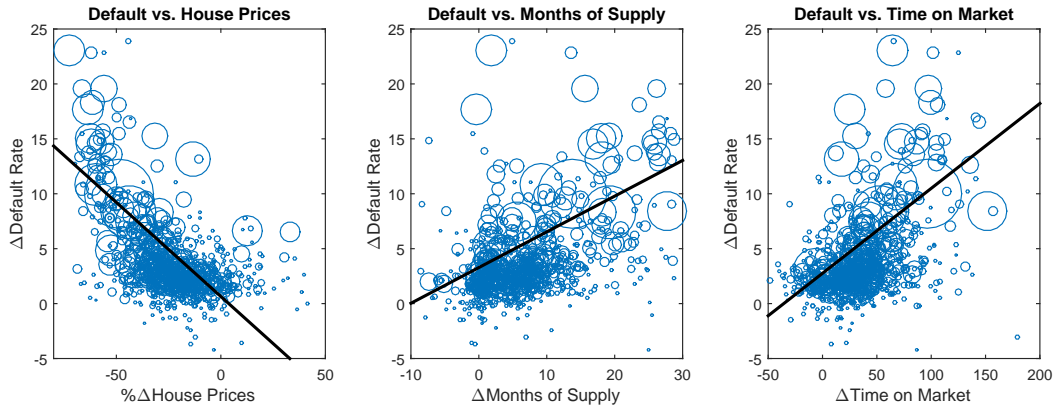


Figure 6: The relationship between mortgage default, house prices, and liquidity. Larger circles represent more populous counties. Sources: (Housing) CoreLogic MLS data. (Default) Equifax serious delinquency rate.

liquidity. Quantitatively, the foreclosure peak is twice as high with endogenous compared to exogenous liquidity *for the same path of house prices* and four times as high once the steeper equilibrium house price decline in the model with endogenous liquidity is taken into account. These results suggest that default is more appropriately characterized by a **liquidity-adjusted double trigger** that broadens the negative equity requirement to include an inability to sell because of severe trading delays from a drop in housing liquidity, regardless of an owner's equity on paper. With this liquidity adjustment, foreclosure propensities conditional on income rise smoothly with leverage—rather than jumping discontinuously at some threshold—as worse debt overhang pressures sellers to set a high list price, thereby jeopardizing the chances of a timely sale and increasing the probability of insolvency. Empirically, figure 6 depicts the standard negative relationship between price appreciation and default. At the same time, the data are consistent with the liquidity-adjusted double trigger by revealing a positive relationship between rising illiquidity and elevated defaults.

Table 5: Amplification Due To Endogenous Liquidity

	Baseline	Exogenous Liquidity*	Amplification
Δ House Prices	-23.4%	-18.6%	25.8%
Δ Consumption	-9.9%	-7.4%	33.6%
Δ Foreclosures	+5.1pp	+1.1pp	343.5%

*The Walrasian model with a 6% seller transaction cost.

$$\Delta\text{DefaultRate}_{06-10}^i = \beta_0 + \beta_1\% \Delta\text{HWNW}_{06-10}^i + \beta_2 \Delta\text{Illiquidity}_{05-08}^i \quad (10)$$

Specification 10 separates out the impact of rising housing illiquidity from falling housing net worth on county-level default rates, where housing net worth is as in Mian et al. (2013), and illiquidity is lagged. Controlling for house price changes, each additional month of time on the market is associated with a 0.81 percentage point rise in default, as shown in appendix table 12.

5.2.2 Amplification and the Transmission from Liquidity to Credit

The deterioration in endogenous housing liquidity deepens the crisis in ways beyond just triggering higher mortgage default. According to table 5, it also amplifies the decline in house prices by over 25% and the drop in consumption by nearly 34%. Conceptually, the value of housing V can be decomposed as

$$V = \text{User Cost (UC)} + \text{Housing Liquidity (HL)} + \text{Credit Liquidity (CL)}. \quad (11)$$

User costs encapsulate implicit rents and future resale value, housing liquidity reflects the premium from ease of selling, and credit liquidity captures the

value of being able to borrow cheaply against the housing collateral.³⁶

$$\sigma_V^2 = \sigma_{UC}^2 + \sigma_{HL}^2 + \sigma_{CL}^2 + 2\sigma_{UC,HL} + 2\sigma_{UC,CL} + 2\sigma_{HL,CL} \quad (12)$$

Now consider the volatility decomposition in equation 12. With exogenous liquidity, $\sigma_{HL}^2 = \sigma_{UC,HL} = \sigma_{HL,CL} = 0$. By contrast, endogenous housing liquidity co-moves positively with economic conditions—i.e. $\sigma_{UC,HL} > 0$ and $\sigma_{HL}^2 > 0$ —and sets off a powerful chain reaction in the mortgage market by creating *liquidity spirals* ($\sigma_{HL,CL} > 0$) à la Brunnermeier and Pedersen (2009). Deteriorating housing liquidity induces lenders to demand higher mortgage premia to compensate for elevated default risk and lower foreclosure recovery ratios.³⁷ This reduction in credit liquidity depresses housing demand, which further harms housing liquidity and creates negative macroeconomic spillovers. The negative empirical relationship between time on the market and adjusted gross income (AGI) shown in figure 7 provides support for this mechanism.

$$\% \Delta Y_{06-11}^i = \beta_0 + \beta_1 \% \Delta \text{HNW}_{06-11}^i + \beta_2 \Delta \text{Illiquidity}_{05-08}^i \quad (13)$$

For further suggestive empirical evidence, equation 13 separately measures the impact of declining county-level housing net worth (as in Mian et al. (2013) and Mian and Sufi (2014)) and rising selling delays on macroeconomic outcomes—specifically, AGI and non-tradable employment.³⁸ Table 13 in the appendix reports the full regression results, showing that the elasticity of AGI

³⁶Formally, housing liquidity is measured by the selling probabilities $\eta_t^{sell}(\cdot)$, and credit liquidity is the price spread between mortgages and risk-free bonds, i.e. $q_t(\cdot)/(1/(1+i_{t+1}))$.

³⁷Formally, lower selling probabilities η_{t+1}^{sell} depress mortgage prices in equation 3 both by increasing the probability of default $(1 - \eta_{t+1}^{sell})d_{t+1}^*$ and by cutting the collateral value of repossessed housing J_{t+1}^{REO} in equation 4, which reduces the foreclosure recovery ratio.

³⁸See section A.3 for methodological details and the complete set of regression results.

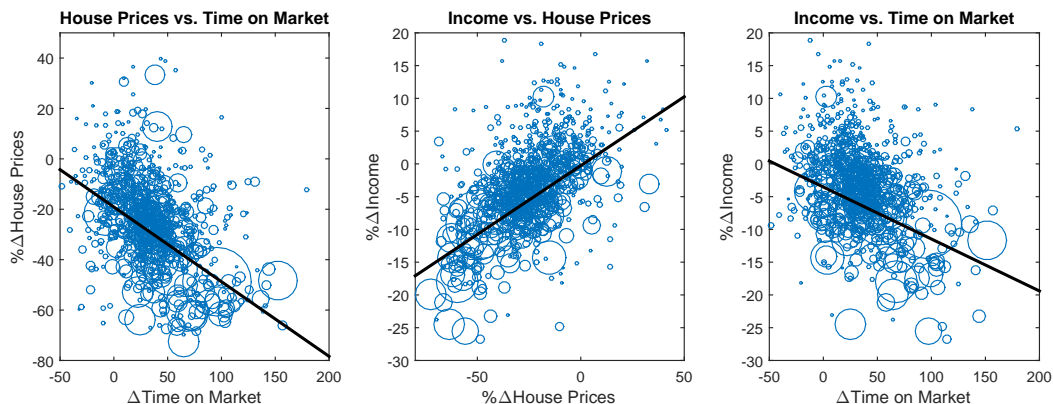


Figure 7: Housing and PCE-deflated adjusted gross income from 2006–2011. Larger circles represent counties with more tax returns in 2006. Sources: (Housing) CoreLogic MLS data. (Income) IRS Statistics of Income.

to housing net worth is 0.24, and the elasticity for nontradable employment is 0.12.³⁹ Incorporating months of supply or average time on the market shrinks both price coefficients and reveals a strong, statistically significant impact of illiquidity. For perspective, the estimates imply a 2 percentage point decline in AGI and more than a 1.5 percentage point drop in nontradable employment associated just with the rise in months of supply during the crisis.

5.2.3 Endogenous Liquidity and the Sales Puzzle

Beyond creating amplification, endogenous housing liquidity also resolves the puzzle surrounding the positive co-movement between house prices and sales. In the Walrasian model here and in much of the literature, lower house prices during downturns spur a counterfactual *surge* in sales as buyers take advantage of greater affordability and expected price growth during the recovery, as in figure 4.⁴⁰ However, the endogenous deterioration in housing liquidity stymies

³⁹Mian et al. (2013) report 0.34 with nondurable consumption from Mastercard data as the dependent variable, and Mian and Sufi (2014) report 0.19 with nontradable employment.

⁴⁰See, for example, Ngai and Sheedy (2015) and Ríos-Rull and Sánchez-Marcos (2012).

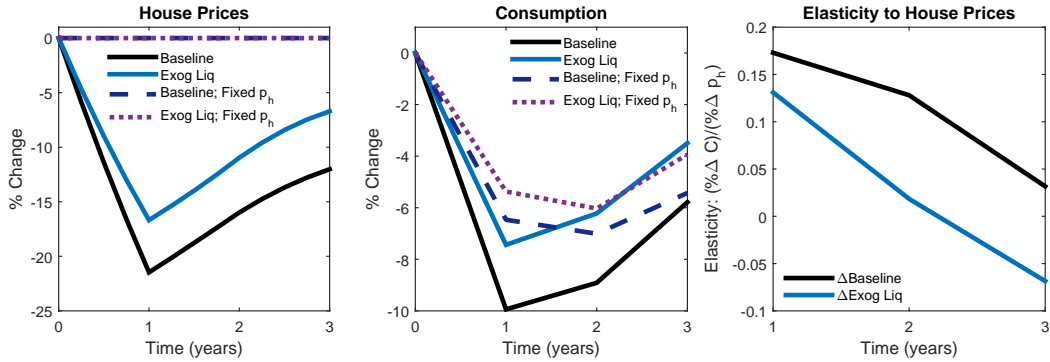


Figure 8: The elasticity of consumption to house prices (calculated as the gap between “baseline” and “fixed p_h ” consumption divided by the drop in prices).

homeowners with long selling delays, which reduces the number of successful transactions. In addition, the contraction of credit induced by liquidity spirals along with the increased riskiness of ownership stems the inflow of buyers.⁴¹

5.3 The Transmission from Housing to Consumption

The macroeconomic amplification in the model and data discussed in section 5.2.2 show that what happens in the housing market does not stay in the housing market. With a focus on consumption, this section goes a step further by investigating the aggregate and cross-sectional nature of housing spillovers.

5.3.1 Aggregate Spillovers

To measure house price spillovers, figure 8 compares aggregate consumption during the crisis to its partial equilibrium path when prices are fixed. The baseline elasticity of consumption to house prices upon impact is 0.17, which is similar to the empirical elasticity of 0.20 from specification 13 with AGI as

⁴¹These effects are strongest in the presence of nonlinearities created by the skewness and credit shocks, which are absent in the business cycle analysis of Hedlund (2016b).

a proxy for consumption. However, the consumption response to house prices is nonlinear and shock-dependent, as shown in appendix figures 34 and 35.

Endogenous liquidity enhances the transmission from house prices to consumption. In relative terms, the consumption elasticity in the Walrasian model starts lower at 0.13 and dissipates more rapidly than in the baseline. In absolute terms, the equilibrium consumption response is 54% larger than the partial equilibrium decline with endogenous liquidity compared to only 38% larger with exogenous liquidity. Even when house prices are held fixed, illiquidity-induced selling delays and debt overhang depress consumption by 20% relative to the Walrasian model, which accounts for much of the 34% amplification in table 5. As empirical support, estimates from specification 14 shown in appendix table 14 associate a \$30 decrease in AGI to every \$1,000 fall in house prices—in line with the literature—and a similar \$31 drop for each one day rise in county-level average time on the market, which amounts to a cumulative \$1,700 based on the total observed increase in selling delays.⁴²

$$\Delta \text{AGI}_{06-11}^i = \beta_0 + \beta_1 \Delta \text{Prices}_{06-11}^i + \beta_2 \Delta \text{Illiquidity}_{05-08}^i \quad (14)$$

5.3.2 Heterogeneity, Tenure Status, and Balance Sheet Depth

These aggregate results mask even richer consumption patterns in the cross section that reveal the importance of household portfolio composition—a point not captured by models with only a consolidated net worth position or where portfolios do not explicitly allow for imbalances to arise between assets and liabilities. Table 6 highlights the role that tenure status and leverage play in driving consumption during the crisis. In both the model

⁴²Mian et al. (2013) and Aladangady (2017) report $\beta_1 \approx 0.05$ for prices to consumption.

Table 6: Who Contributed Most to the Consumption Decline?

	Renters	Owners	Low LTV	High LTV
<i>Model</i>				
Pre-Crisis Share	16.0%	84.0%	18.9%	19.0%
Share of Decline	6.2%	93.8%	5.4%	28.9%
<i>Data</i>				
Pre-Crisis Share	23.9%	76.1%	13.4%	13.2%
Share of Decline	5.1%	94.9%	8.4%	22.3%

Source: PSID using the sampling criteria of Arellano et al. (2017) and re-weighted to match the distribution of renters, owners, low LTV, and high LTV households from the 2007 SCF. Low loan-to-value (LTV) is below 0.3; high LTV is above 0.8.

and data, owners—who have higher income on average than renters—account for a disproportionate share of pre-crisis consumption. However, despite this higher income, they comprise an even larger share of the consumption *decline* during the crisis. The impact of mortgage debt is even more pronounced, with highly leveraged owners accounting for a dramatically higher share of the aggregate consumption decline than their pre-crisis share reflects.⁴³

Tenure status and leverage are both related to the concept of **balance sheet depth**, which refers to the size of households' *gross*, rather than net, portfolio positions. By reducing the value of assets without altering liabilities, the collapse in house prices induces more severe consumption declines for households possessing deeper and more illiquid balance sheets—that is, larger houses coupled with larger mortgages—as seen in table 7.⁴⁴ As a stark case, highly leveraged owners in the model (data) experience a 16% (13.4%) drop in

⁴³These results are consistent with the link between leverage, house prices, and consumption found at various levels of geographic aggregation in Mian et al. (2013), Dynan (2012), DiMaggio, Kermani, Keys, Piskorski, Ramcharan, Seru and Yao (2017), Aladangady (2017), and Jones, Midrigan and Philippon (2018).

⁴⁴Figure 37 in the appendix also depicts the importance of balance sheet depth.

Table 7: Consumption, Net Worth, and Balance Sheet Depth

	<i>Low NW-By Tenure</i>		<i>Medium NW-Owners</i>		<i>High NW-Owners</i>	
	Renters	Owners	Small h	Medium h	Medium h	Large h
<i>Model</i>						
Δ Consumption	-5.1%	-16.0%	-11.8%	-22.3%	-5.7%	-8.9%
Pre-Crisis LTV	—	84.8%	65.2%	82.3%	31.5%	58.8%
<i>Data</i>						
Δ Consumption	-5.5%	-13.4%	-7.4%	-30.8%	-1.8%	-7.3%
Pre-Crisis LTV	—	80.9%	75.4%	93.6%	40.1%	55.0%

Net worth (NW) = liquid assets + housing – mortgage debt. Source: PSID using the sampling criteria of [Arellano et al. \(2017\)](#).

consumption, which far exceeds the 5.1% (5.5%) decline by those renters who have similar net worth but shallower and more liquid balance sheets.

The impact of balance sheets on consumption behavior extends to higher order moments as well. While owners experience less consumption volatility than renters prior to the housing bust—owing in part to positive selection by income, but also because of the consumption smoothing benefits of access to equity extraction in the mortgage market—the risk-sharing advantages of ownership evaporate during the crisis, as seen in figure 38. Specifically, the homeowner consumption growth distribution shifts down and fans to the left, whereas renters do not exhibit this consumption skewness. Similar patterns emerge between highly leveraged borrowers and their less indebted counterparts, while financially distressed owners attempting to avoid foreclosure suffer the worst declines in consumption. By contrast, owners who immediately trigger the default option to discharge their debt experience a milder drop in consumption, albeit at the expense of losing their house and access to credit. Lastly, the transmission from housing to consumption through balance sheets is also impacted by endogenous housing liquidity. As seen in appendix figure 36, the consumption of renters behaves similarly in the baseline

Table 8: Effects of Mortgage Rate Reductions

	<i>House Prices</i>		<i>Consumption</i>	
	Change	Recovery	Change	Recovery
<i>Surprise</i>				
Fixed Prices	—	—	+0.7pp	12.9%
Equilibrium	+5.3pp	47.2%	+1.7pp	30.0%
<i>Pre-Announced</i>				
Fixed Prices	—	—	+1.1pp	18.9%
Equilibrium	+4.4pp	39.6%	+1.5pp	25.5%

“Change” shows the policy impact *upon implementation*.

“Recovery” shows how much of the gap is closed by the policy, i.e. $100 \times (x_{policy,t} - x_{baseline,t}) / (x_{pre-bust} - x_{baseline,t})$.

and Walrasian economies, whereas the negative effects of debt overhang and amplification from selling delays increase with levels of leverage and distress.

5.4 The Power of Mortgage Rate Reductions

With house prices in free fall and short-term interest rates at the zero lower bound, officials between late 2008 and the end of 2014 pursued a series of policies—from forward guidance to large scale purchases of mortgage-backed securities—to lower long-term rates, repair household balance sheets, and arrest the crisis.⁴⁵ This section quantifies the macroeconomic impact of lowering mortgage rates and its transmission through the housing market. The persistent 1.5 percent observed mortgage rate decline is implemented in the model via an exogenous, unanticipated reduction in servicing costs ϕ_t

⁴⁵See Hamilton (2018), Kuttner (2018), and Gagnon and Sack (2018) provide a more detailed summary of these policies. A growing body of work attributes much of the subsequent drop in mortgage rates to these policies. See, for example, Krishnamurthy and Vissing-Jorgensen (2011), Gagnon, Raskin, Remache and Sack (2011), Joyce, Miles, Scott and Vayanos (2012), Hancock and Passmore (2014), Engen, Laubach and Reifschneider (2015), Bonis, Ihrig and Wei (2017), and Fieldhouse, Mertens and Ravn (2018).

beginning two years into the crisis.⁴⁶ When implemented by surprise in this way, the reduction in rates accelerates the recovery by closing the gap between the contemporaneous and pre-crisis levels in house prices and consumption by 47.2% and 30.0%, respectively, according to table 8.

Counterfactually announcing the rate reduction ahead of time creates an immediate though attenuated rise in consumption, but how can such a boost occur prior to the actual realization of lower borrowing costs? The answer lies in the balance sheet transmission from house prices to consumption. Figure 39 shows that, when house prices are held fixed, consumption does not react to the pre-announcement. In this scenario, consumption only increases upon implementation of the lower rates once borrowers gain access to cheaper equity extraction. However, in equilibrium, house prices respond immediately to the pre-announcement because of higher expected future appreciation, which restores household balance sheets and causes consumption to rise in concert.

Table 8 quantifies this balance sheet transmission channel in both cases. For the surprise implementation, 59% (1.0pp out of 1.7pp) of the consumption boost comes from balance sheet repair caused by higher house prices and only 41% from all other channels, such as intertemporal substitution and cash-flow effects. The impact of mortgage rate reductions on consumption also varies significantly in the cross section, with figure 40 in the appendix showing that highly leveraged owners experience a large 2.9 percentage point consumption boost compared to only 1.2 percentage points for less indebted owners.

⁴⁶The shock lasts for 5 years to align with the large scale asset purchases from 2009–2014. Figure 15 shows mortgage rates in the model and data. If explicitly financed by government purchases, the cumulative fiscal cost of such a rate reduction in the model amounts to 20% of annual goods output, which is just below empirical estimates of 25%–29% of GDP from Kuttner (2018), Hamilton (2018), and Gagnon and Sack (2018).

6 Conclusion

The quantitative analysis points to credit supply shocks and higher downside risk from a deterioration in earnings skewness as the key drivers of the housing crash and slow recovery. In addition, evidence from the model and data establishes the importance of endogenous housing liquidity and balance sheet depth as sources of macroeconomic amplification and propagation. To capture the imbalances and fragility created during periods of large price swings, these results suggest that the new paradigm for structural macroeconomic models should explicitly include liquid short-term saving and endogenously illiquid housing collateralized by long-term loans. Fruitful avenues for future research include exploring the underlying causes of earnings skewness and credit supply shocks, for example by explicitly incorporating a frictional labor market with time-varying unemployment or by integrating recent advances in quantitative banking models that allow for credit rationing and bank balance sheet constraints. In addition to the macroeconomic channels of transmission through the housing market discussed in this paper, these extensions may have important implications for monetary policy and macroprudential regulation.

References

- Adelino, Manuel, Antoinette Schoar, and Felipe Severino**, “Loan Originations and Defaults in the Mortgage Crisis: The Role of the Middle Class,” *Review of Financial Studies*, 2016, 29 (7), 1635–1670.
- Aladangady, Aditya**, “Housing Wealth and Consumption: Evidence from Geographically Linked Microdata,” *American Economic Review*, 2017, 107 (11), 3415–3446.

- Albanesi, Stefania, Giacomo DeGiorgi, and Jaromir Nosal**, “Credit Growth and the Financial Crisis: A New Narrative,” 2017. Working Paper.
- Anenberg, Elliot and Edward Kung**, “Interest Rates and Housing Market Dynamics in a Housing Search Model,” 2019. Working Paper.
- Arellano, Cristina, Yan Bai, and Patrick Kehoe**, “Financial Frictions and Fluctuations in Volatility,” *Journal of Political Economy*, Forthcoming 2019.
- Arellano, Manuel, Richard Blundell, and Stéphane Bonhomme**, “Earnings and Consumption Dynamics: A Nonlinear Panel Data Framework,” *Econometrica*, May 2017, *85* (3), 693–734.
- Avery, Robert B., Neil Bhutta, Kenneth P. Brevoort, Glenn B. Canner, and Christa N. Gibbs**, “The 2008 HMDA Data: The Mortgage Market during a Turbulent Year,” *Federal Reserve Bulletin*, 2010.
- Bachmann, Rudiger and Daniel Cooper**, “The Ins and Arouns in the U.S. Housing Market,” 2014. Working Paper.
- Bajari, Patrick, Phoebe Chan, Dirk Krueger, and Daniel Miller**, “A Dynamic Model of Housing Demand: Estimation and Policy Implications,” *International Economic Review*, 2013, *54* (2), 409–442.
- Berger, David and Joseph Vavra**, “Consumption Dynamics During Recessions,” *Econometrica*, 2015, *83* (1), 101–154.
- , **Ian Dew-Becker, and Stefano Giglio**, “Uncertainty Shocks as Second-Moment News Shocks,” *Review of Economic Studies*, Forthcoming 2019.

- , **Veronica Guerrieri, Guido Lorenzoni, and Joseph Vavra**, “House Prices and Consumer Spending,” *Review of Economic Studies*, 2018, *85* (3), 1502–1542.
- Bhutta, Neil**, “The Ins and Outs of Mortgage Debt During the Housing Boom,” *Journal of Monetary Economics*, 2015, *76*, 284–298.
- Bloom, Nicholas, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J. Terry**, “Really Uncertain Business Cycles,” *Econometrica*, 2018, *86* (3), 1031–1065.
- Bonis, Brian, Jane Ihrig, and Min Wei**, “The Effect of the Federal Reserve’s Securities Holdings on Longer-term Interest Rates,” *FEDS Notes*, 2017.
- Brunnermeier, Markus K. and Lasse Heje Pedersen**, “Market Liquidity and Funding Liquidity,” *Review of Financial Studies*, 2009, *22* (6), 2201–2238.
- Campbell, John Y. and João F. Cocco**, “A Model of Mortgage Default,” *Journal of Finance*, 2015, *70* (4), 1495–1554.
- Caplin, Andrew and John Leahy**, “Trading Frictions and House Price Dynamics,” *Journal of Money, Credit, and Banking*, 2011, *43*, 283–303.
- Castañeda, Ana, Javier Díaz-Giménez, and José-Víctor Ríos-Rull**, “Accounting for the U.S. Earnings and Wealth Inequality,” *Journal of Political Economy*, 2003, *111* (4), 818–857.
- Cheng, Ing-Haw, Sahil Raina, and Wei Xiong**, “Wall Street and the Housing Bubble,” *American Economic Review*, 2014, *104* (9), 2797–2829.

- Corbae, Dean and Erwan Quintin**, “Leverage and the Foreclosure Crisis,” *Journal of Political Economy*, 2015, 123, 1–65.
- Cox, Josue and Sydney C. Ludvigson**, “Drivers of the Great Housing Boom-Bust: Credit Conditions, Beliefs, or Both?,” Nov. 2018. Working Paper.
- Davis, Morris A., Andreas Lehnert, and Robert F. Martin**, “The Rent-Price Ratio for the Aggregate Stock of Owner-Occupied Housing,” *Review of Income and Wealth*, 2008, 54 (2), 279–284.
- , **William D. Larson, and Stephen D. Oliner**, “Mortgage Risk Since 1990,” 2019. Working Paper.
- Davis, Morris and Stijn Van Nieuwerburgh**, “Housing, Finance and the Macroeconomy,” *Handbook of Regional and Urban Economics, Volume 5*, 2015, pp. 753–811.
- Díaz, Antonia and Bélen Jerez**, “House Prices, Sales, and Time on the Market: A Search-Theoretic Framework,” *International Economic Review*, 2013, 54 (3), 837–872.
- **and María-José Luengo-Prado**, “The Wealth Distribution with Durable Goods,” *International Economic Review*, Feb. 2010, 51 (1), 143–170.
- DiMaggio, Marco, Amir Kermani, Benjamin J. Keys, Tomasz Piskorski, Rodney Ramcharan, Amit Seru, and Vincent Yao**, “Interest Rate Pass-Through: Mortgage Rates, Household Consumption, and Voluntary Deleveraging,” *American Economic Review*, 2017, 107 (11), 3550–3588.

- Driscoll, John C., Benjamin S. Kay, and Cindy M. Vojtech**, “The Real Consequences of Bank Mortgage Lending Standards,” 2016. Working Paper.
- Dynan, Karen**, “Is a Household Debt Overhang Holding Back Consumption?,” *Brookings Papers on Economic Activity*, Spring 2012.
- Engen, Eric N., Thomas Laubach, and David Reifschneider**, “The Macroeconomic Effects of the Federal Reserve’s Unconventional Monetary Policies,” 2015. Working Paper.
- Favilukis, Jack, Sydney C. Ludvigson, and Stijn Van Nieuwerburgh**, “The Macroeconomic Effects of Housing Wealth, Housing Finance, and Limited Risk-Sharing in General Equilibrium,” *Journal of Political Economy*, 2017, 125 (1), 140–223.
- Fernald, John**, “Productivity and Potential Output Before, During, and After the Great Recession,” *NBER Macroeconomics Annual*, 2014.
- Fieldhouse, Andrew J., Karel Mertens, and Moren O. Ravn**, “The Macroeconomic Effects of Government Asset Purchases: Evidence from Postwar U.S. Housing Credit Policy,” *The Quarterly Journal of Economics*, 2018, 133 (3), 1503–1560.
- Flavin, Marjorie and Shinobu Nakagawa**, “A Model of Housing in the Presence of Adjustment Costs: A Structural Interpretation of Habit Persistence,” *American Economic Review*, Mar. 2008, 98 (1), 474–495.
- Foote, Christopher L., Lara Loewenstein, and Paul S. Willen**, “Cross-Sectional Patterns of Mortgage Debt during the Housing Boom: Evidence and Implications,” 2016. Working Paper.

- Gagnon, Joseph E. and Brian Sack**, “QE: A User’s Guide,” *Peterson Institute for International Economics Policy Brief*, 2018.
- Gagnon, Joseph, Matthew Raskin, Julie Remache, and Brian Sack**, “The Financial Market Effects of the Federal Reserve’s Large-Scale Asset Purchases,” *International Journal of Central Banking*, 2011, 7 (1), 3–43.
- Garriga, Carlos**, “Lending Standards in Mortgage Markets,” *Federal Reserve Bank of St. Louis Economic Synopses*, 2009.
- **and Aaron Hedlund**, “Housing Finance, Boom-Bust Episodes, and Macroeconomic Fragility,” 2018. Working Paper.
- , **Rody Manuelli, and Adrian Peralta-Alva**, “A Macroeconomic Model of Price Swings in the Housing Market,” *American Economic Review*, Forthcoming 2019.
- Gerardi, Kristopher, Andreas Lehnert, Shane M. Sherlund, and Paul Willen**, “Making Sense of the Subprime Crisis,” *Brookings Papers on Economic Activity*, Fall 2008.
- , – , – , **and –** , “Making Sense of the Subprime Crisis,” *Brookings Papers on Economic Activity*, 2008.
- , **Kyle F. Herkenhoff, Lee E. Ohanian, and Paul S. Willen**, “Can’t Pay or Won’t Pay? Unemployment, Negative Equity, and Strategic Default,” *Review of Financial Studies*, 2018, 31 (3).
- Glaesar, Edward L. and Joseph Gyourko**, “Arbitrage in Housing Markets,” Jan. 2007. Working Paper.

- Glover, Andrew, Jonathan Heathcote, Dirk Krueger, and José-Víctor Ríos-Rull**, “Intergenerational Redistribution in the Great Recession,” 2019. Working Paper.
- Gruber, Joseph and Robert F. Martin**, “The Role of Durable Goods in the Distribution of Wealth: Does Housing Make Us Less Equal?,” 2003. Working Paper.
- Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song**, “What Do Data on Millions of U.S. Workers Reveal about Life-Cycle Earnings Dynamics?,” 2019. Working Paper.
- , **Serdar Ozkan, and Jae Song**, “The Nature of Countercyclical Income Risk,” *Journal of Political Economy*, 2014, 122 (3), 621–660.
- Halket, Jonathan, Lars Nesheim, and Florian Oswald**, “The Housing Stock, Housing Prices, and User Costs: The Roles of Location, Structure and Unobserved Quality,” 2017. Working Paper.
- Hamilton, James D.**, “The Efficacy of Large-Scale Asset Purchases When the Short-Term Interest Rate is at its Effective Lower Bound,” *Brookings Papers on Economic Activity*, Fall 2018.
- Hancock, Diana and Wayne Passmore**, “How the Federal Reserve’s Large-Scale Asset Purchases (LSAPs) Influence Mortgage-Backed Securities (MBS) Yields and U.S. Mortgage Rates,” 2014. Working Paper.
- Handley, Kyle and J. Frank Li**, “Measuring the Effects of Firm Uncertainty on Economic Activity: New Evidence from One Million Documents,” 2018. Working Paper.

- Head, Allen, Huw Lloyd-Ellis, and Hongfei Sun**, “Search, Liquidity, and the Dynamics of House Prices and Construction,” *American Economic Review*, 2014, *104* (4), 1172–1210.
- Hedlund, Aaron**, “Illiquidity and its Discontents: Trading Delays and Foreclosures in the Housing Market,” *Journal of Monetary Economics*, 2016, *83*, 1–13.
- , “The Cyclical Dynamics of Illiquid Housing, Debt, and Foreclosures,” *Quantitative Economics*, Mar. 2016, *7* (1), 289–328.
- Herkenhoff, Kyle and Lee Ohanian**, “The Impact of Foreclosure Delay on U.S. Employment,” *Review of Economic Dynamics*, January 2019, pp. 63–83.
- Iacoviello, Matteo and Marina Pavan**, “Housing and Debt Over the Life Cycle and Over the Business Cycle,” *Journal of Monetary Economics*, 2013, *60* (2), 221–238.
- Jones, Callum, Virgiliu Midrigan, and Thomas Philippon**, “Household Leverage and the Recession,” 2018. Working Paper.
- Joyce, Michael, David Miles, Andrew Scott, and Dimitri Vayanos**, “Quantitative Easing and Unconventional Monetary Policy – An Introduction,” *The Economic Journal*, Nov. 2012, pp. 271–288.
- Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng**, “Measuring Uncertainty,” *American Economic Review*, 2015, *105* (3), 1177–1216.
- Justiniano, Alejandro, Giorgio Primiceri, and Andrea Tambalotti**, “Household Leveraging and Deleveraging,” *Review of Economic Dynamics*, 2015, *18* (1), 3–20.

- Kahn, James A.**, “What Drives Housing Prices?,” June 2009. Working Paper.
- Kaplan, Greg, Kurt Mitman, and Giovanni L. Violante**, “The Housing Boom and Bust: Model Meets Evidence,” 2019. Working Paper.
- Kozeniauskas, Nicholas, Anna Orlik, and Laura Veldkamp**, “What Are Uncertainty Shocks?,” 2018. Working Paper.
- Krishnamurthy, Arvind and Annette Vissing-Jorgensen**, “The Effects of Quantitative Easing on Interest Rates: Channels and Implications for Policy,” *Brookings Papers on Economic Activity*, Fall 2011, pp. 215–288.
- Kuhn, Moritz and José-Víctor Ríos-Rull**, “2013 Update on the U.S. Earnings, Income, and Wealth Distributional Facts: A View from Macroeconomics,” 2013. Working Paper.
- Kuttner, Kenneth N.**, “Outside the Box: Unconventional Monetary Policy in the Great Recession and Beyond,” *Journal of Economic Perspectives*, 2018, 32 (4), 121–146.
- Landvoigt, Tim, Monika Piazzesi, and Martin Schneider**, “The Housing Market(s) of San Diego,” *American Economic Review*, 2015, 105 (4), 1371–1407.
- Lee, Donghoon, Christopher Mayer, and Joseph Tracy**, “A New Look at Second Liens,” in Edward L. Glaeser and Todd Sinai, eds., *Housing and the Financial Crisis*, 2013.
- Leventis, Andrew**, “The Relationship between Second Liens, First Mortgage Outcomes, and Borrower Credit: 1996 – 2010,” 2014. Working Paper.

- Levitin, Adam J. and Susan M. Wachter**, “Second Liens and the Leverage Option,” *Vanderbilt Law Review*, 2015, 68 (5), 1243–1294.
- Mian, Atif and Amir Sufi**, “What Explains the 2007–2009 Drop in Employment?,” *Econometrica*, 2014, 82 (6), 2197–2223.
- , **Kamalesh Rao, and Amir Sufi**, “Household Balance Sheets, Consumption, and the Economic Slump,” *Quarterly Journal of Economics*, 2013, 128 (4), 1687–1726.
- Ngai, L. Rachel and Kevin D. Sheedy**, “The Ins and Outs of Selling Houses,” 2015. Working Paper.
- **and Silvana Tenreyro**, “Hot and Cold Seasons in the Housing Market,” *American Economic Review*, 2014, 104 (12), 3991–4026.
- Pennington-Cross, Anthony**, “The Value of Foreclosed Property,” *JRER*, 2006, 28 (2), 193–214.
- Piazzesi, Monika and Martin Schneider**, “Momentum Traders in the Housing Market: Survey Evidence and a Search Model,” *American Economic Review: Papers & Proceedings*, 2009, 99 (2), 406–411.
- **and** – , “Housing and Macroeconomics,” *Handbook of Macroeconomics, Volume 2*, 2016, pp. 1547–1640.
- , – , **and Johannes Stroebel**, “Segmented Housing Search,” *American Economic Review*, Forthcoming 2019.
- Ríos-Rull, José-Víctor and Virginia Sánchez-Marcos**, “Aggregate Shocks and House Price Fluctuations,” 2012. mimeo.

- Salgado, Sergio, Fatih Guvenen, and Nicholas Bloom**, “Skewed Business Cycles,” 2017. Working Paper.
- Shoag, Daniel and Stan Veuger**, “Uncertainty and the Geography of the Great Recession,” *Journal of Monetary Economics*, 2016, *84*, 84–93.
- Sommer, Kamila, Paul Sullivan, and Randal Verbrugge**, “The Equilibrium Effect of Fundamentals on House Prices and Rents,” *Journal of Monetary Economics*, 2013, *60* (7), 854–870.
- Stock, James H. and Mark W. Watson**, “Disentangling the Channels of the 2007 – 2009 Recession,” *Brookings Papers on Economic Activity*, Spring 2012.
- Storesletten, Kjetil, Chris I. Telmer, and Amir Yaron**, “Cyclical Dynamics in Idiosyncratic Labor Market Risk,” *Journal of Political Economy*, June 2004, *112* (3), 695–717.
- Wheaton, William C.**, “Vacancy, Search, and Prices in a Housing Market Matching Model,” *The Journal of Political Economy*, Dec. 1990, *98* (6), 1270–1292.

A Data Appendix

The detailed micro data used in the scatter plots, heat maps, and regressions throughout the paper come from several sources. This section explains the construction of each variable, provides summary statistics, and compares the aggregate dynamics of house prices and liquidity from the CoreLogic MLS housing data to those constructed from public sources. In addition, this section presents tables with the full cross-sectional regression results.

A.1 Variable Construction

Table 9: Summary of Data Sources

Variable	Source	Raw Data Aggregation
House Prices	CoreLogic MLS	Listing Level
Housing Liquidity*	CoreLogic MLS	Listing Level
Mortgage Default	Equifax	Loan Level
Adjusted Gross Income	IRS SOI	Zip Code Level
Employment	BLS QCEW	County Level
Nontradable Employment	Census CBP	County Level

*Includes both time on the market and months of supply.

Table 9 summarizes the data sources. Housing variables are constructed from listings-level CoreLogic MLS data, loan-level credit data from Equifax is used to measure mortgage default, the IRS Statistics of Income provides income data at the zip code level, and county-level employment comes from a combination of the BLS Quarterly Census of Employment and Wages (all industries) and the Census County Business Patterns (industry specific to construct nontradable employment). National Flow of Funds data is also used to construct the housing net worth shock variable originally from [Mian et al. \(2013\)](#) that appears in some of the regressions.

A.1.1 House Prices and Liquidity

The MLS data is part of the CoreLogic Real Estate Database, which contains property-level information on listings and sales—among other variables—for residential properties around the U.S drawn from organizations of real estate agents who enter properties into an electronic MLS system in order to market them. The MLS dataset is dynamic by tracking changes in each listing over time—especially whether the property is pulled off the market and re-listed, which is a common seller tactic to move their listing to the top of the search queue for potential buyers. The dataset includes a large array of fields, but most important for the analysis in this paper is the date each property went on the market, any history of de-listings and re-listings, and the final closing price and date. The analysis is restricted to single family homes and condominiums.

House Prices House prices are the MLS transaction price at closing. This data is then adjusted for inflation using the PCE and aggregated to the county level. Counties with fewer than ten transactions in a given year are excluded.

Time on the Market Time on the market is measured as the *total* number of days a property is actively on the market before selling. However, the actual selling process for a property may entail multiple episodes of listing and de-listing, each instance of which shows up as a separate entry in the raw data. For example, a property could be listed for a duration of 6 months without selling, then pulled off the market for 1 month, and subsequently re-listed and sold 2 months later. In such a case, the raw data reports a failed listing that lasts for 6 months followed by a successful listing that takes 2 months. By contrast, the view in this paper is that the property has taken 8 months to sell. More generally, to capture the effective time that properties are listed before selling or being pulled off the market for good, the measure of time on the market in this paper strings together all failed listings that are separated by less than 3 months and adds them to the terminal listing that culminates either in a sale or more permanent removal. The vast majority of de-listings and re-listings occur within a 3 month horizon, which motivates this choice of threshold for distinguishing between strategic seller behavior and genuine instances of sellers removing their property from the market (e.g. to make home improvements or wait for a better selling environment).

Months of Supply Months of supply is the number of houses on the market in each county divided by the seasonally adjusted annualized sales rate in that county. Thus, whereas time on the market is a listing-level variable that can be aggregated manually to measure housing illiquidity in a broader geography, months of supply is intrinsically a market-level illiquidity measure.

Comparisons to Publicly Available Housing Data Presently, there is no publicly available county-level data that extends back to before the crisis began in 2006 to compare with the CoreLogic MLS data.⁴⁷ However, publicly available *national* data on house prices and illiquidity shown in figure 9 serves as a useful benchmark to assess the MLS data. In particular, real house prices in the MLS follow a similar though slightly exaggerated trajectory to the paths of the inflation-adjusted house price indices from the Federal Housing Finance Agency (FHFA) and Case-Shiller. Furthermore, months of supply in the MLS closely tracks its counterparts from the Census and National Association of Realtors (NAR) for new houses and existing houses, respectively.

A.1.2 Mortgage Default

The Equifax Credit Bureau Database (FRBNY Consumer Credit Panel) contains loan-level data on households' credit reports. The data is a representative 5% sample of individuals in the United States with a credit report and Social Security Number and is reported on a quarterly basis. To coincide with the other variables in the regressions, the data is aggregated to the county level. Important to the construction of the housing net worth

⁴⁷For example, public county-level data from Zillow for days on the market begins in 2010.

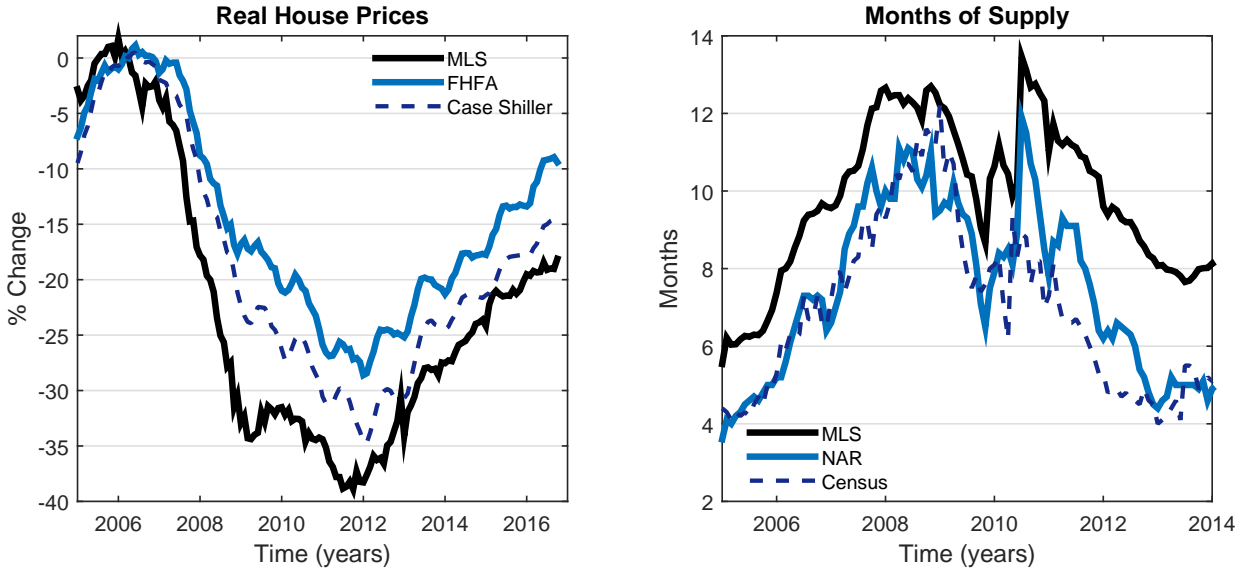


Figure 9: Comparison of national MLS data with publicly available sources. (Left) MLS average transaction price vs. FHFA purchase-only index vs. Case-Shiller index (all deflated by the PCE). (Right) MLS vs. National Association of Realtors (existing houses) vs. Census (new houses). Months of supply is the number of houses on the market divided by monthly sales.

shock discussed below, the data contain information on the size of outstanding balances for many types of household debt, especially mortgages. In addition, the data provide several measures of mortgage payment status, including whether a loan is current, past due, or severely derogatory and heading toward foreclosure, which is this paper’s preferred measure of mortgage default.

A.1.3 Income

The IRS Statistics of Income (SOI) dataset provides zip code level information for selected income and tax items. The data are based on individual tax returns taken from forms 1040, 1040A, and 1040EZ filed with the IRS. If a taxpayer files returns for multiple years at any given time, only the most recent return is included. A zip-to-county crosswalk from HUD is then used to convert this data to the county level, thereby making it consistent with the other variables in this paper’s analysis. From this data, the primary object of interest is adjusted gross income, but the non-wage component of income—which subsumes income from interest, dividends, and capital gains—is used to approximate county-level assets during the construction of the housing net worth shock variable described below.

A.1.4 Employment

The Quarterly Census of Employment and Wages (QCEW) from the BLS publishes a quarterly count of employment and wages reported by employers covering more than 95 percent of U.S. jobs at various degrees of geographic disaggregation down to the county level.

This paper relies on the QCEW for its measure of **total employment** in each county. As a supplement, the Census County Business Patterns (CBP) gives detailed industry-specific county-level employment data. This paper then constructs **nontradable employment** for each county by assigning industries according to their 4-digit NAICS classification using the criteria in Mian and Sufi (2014).

A.1.5 Housing Net Worth Shock

Constructing the housing net worth shock from Mian et al. (2013) and Mian and Sufi (2014) requires a pre-crisis measure of county-level net worth in 2006: $NW_{06} = A_{06} + H_{06} - D_{06}$, where NW is net worth, A is financial assets, H is housing wealth, and D is total household debt. No data exists for the county-level *stock* of assets, but it can be approximated as each county’s share of total asset *income* (i.e. IRS non-wage income a_{06}^i for county i) multiplied by the Flow of Funds aggregate stock of financial assets: $A_{06} = \frac{a_{06}^i}{\sum_j a_{06}^j} A_{06}^{FOF}$. Housing wealth is calculated as the county-level 2006 average MLS price multiplied by the number of *owner-occupied* units in the county interpolated between the Census 2000 and 2010 values: $H_{06} = \sum_j p_{06}^j n_{06}^{j,own}$. To construct the measure of debt and correct for possible under-reporting in small counties, the cumulative debt balance *per borrower* in 2006 for each county is scaled up by the *total* number of households in the county interpolated from the Census 2000 and 2010 values: $D_{06} = \sum_j d_{06}^j n_{06}^{j,tot}$. Table 10 shows that the constructed aggregates from the merged sample mirror the direct Flow of Funds measures.⁴⁸

Table 10: Aggregate Net Worth Ratios

Ratio	Merged Sample	Flow of Funds
A_{06}/NW_{06}	0.83	0.76
H_{06}/NW_{06}	0.32	0.34
D_{06}/NW_{06}	0.15	0.20

The housing net worth shock between 2006 and 2011 in county i is then defined as the percentage house price change multiplied by the housing net worth share, i.e. $\% \Delta HNW_{06,t}^i = \% \Delta \text{Prices}_{06,t}^i \times \frac{H_{06}^i}{NW_{06}^i}$.⁴⁹

A.2 Descriptive Statistics and Figures

This section provides supplemental information to what section 2 covers regarding the behavior of key variables during the housing crash. In particular, table 11 provides summary statistics from the peak of the pre-crisis to its trough for housing, credit, and macroeconomic variables of interest. The data reveal both the aggregate severity of the crisis and the large degree of variation.

⁴⁸Flow of Funds: (A_{06}) FL154090005Q. (H_{06}) LM155035015Q. (D_{06}) FL154190005Q. (NW_{06}) FL152090005Q. The cleaned merged data are winsorized above the 95th percentile of H_{06}^i/NW_{06}^i to correct for exaggerated 2006 housing values in the MLS relative to Census.

⁴⁹The 2006–2009 time window in Mian et al. (2013) stops prior to the house price trough.

Table 11: Summary Statistics (Peak-Trough 2006–2011)

	Obs	Mean	St. Dev.	10th	Median	90th
House Prices (% Δ)	7,570	-36.64	20.71	-63.59	-35.73	-11.63
Months Supply (Δ Months)	7,261	10.57	11.98	0.53	6.83	26.05
Time on Market (Δ Days)	7,269	53.71	38.33	10.42	50.78	101.37
Mortgage Default (Δ pp)	7,047	5.32	4.99	0.90	3.84	12.08
Adjusted Gross Income (% Δ)	7,519	-6.52	11.40	-16.00	-6.26	1.43
Employment* (% Δ)	1,496	-5.92	4.54	-12.04	-6.07	-0.57
Nontradable Employment* (% Δ)	1,496	-5.26	7.45	-10.94	-6.50	2.96

*County level. All other statistics are at the zip-code level. Δ = change; % Δ = percent change. Sources: (Income) IRS Statistics of Income deflated by PCE. (Employment) BLS Quarterly Census of Employment and Wages. (Nontradable Employment) Census County Business Patterns. (House Prices, Months Supply, Time on Market) CoreLogic MLS. House prices deflated by PCE. (Mortgage Default) Equifax. MLS statistics are sales-weighted. All other statistics are population-weighted.

Figure 10 supplements the empirical evidence in section 5 that supports the mechanisms described in the model whereby house prices and liquidity transmit to the rest of the macroeconomy. Specifically, the left column of panels is consistent with the findings in Mian et al. (2013) and Mian and Sufi (2014) that associate larger house price declines with worse macroeconomic outcomes. However, the remaining two columns show that prices provide only a limited view of the negative housing spillovers during the crisis. In particular, deteriorations in housing liquidity measured either by rising months of supply or time on the market are associated with significant declines in income and employment at the county level throughout the country.

Recall the heat maps from section 2 that show a clear geographic pattern between the decline in house prices, the fall in income, the spike in mortgage default, and the rise in housing *illiquidity* at the county level, using months of supply as the measure. The heat maps in figures 11 and 12 confirm that the same patterns arise when using time on the market as the measure of illiquidity instead. Furthermore, the map in figure 13 reveals a strong association between the decline in income and employment, suggesting that both are good proxies for the poor performance of the macroeconomy during the housing bust.

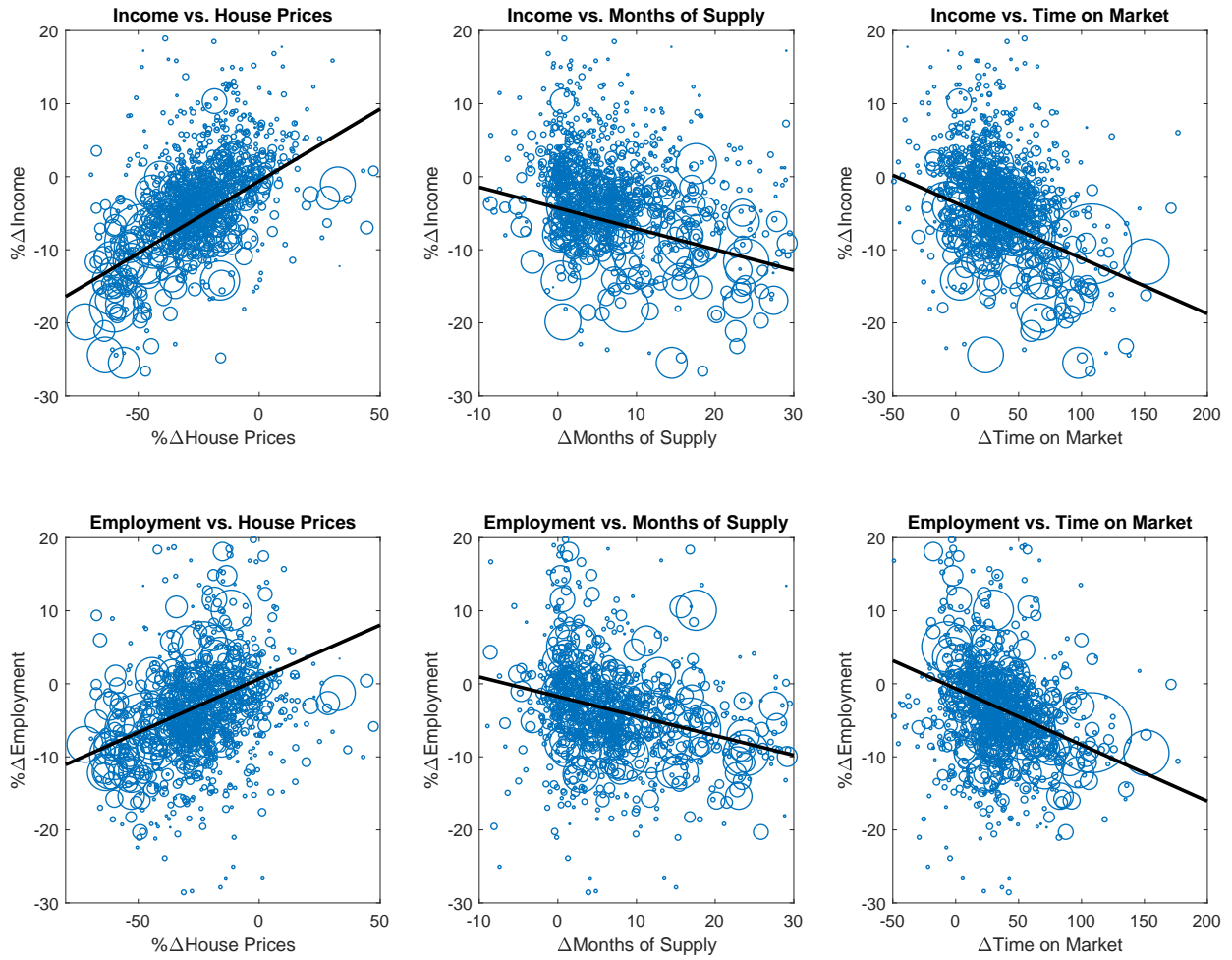
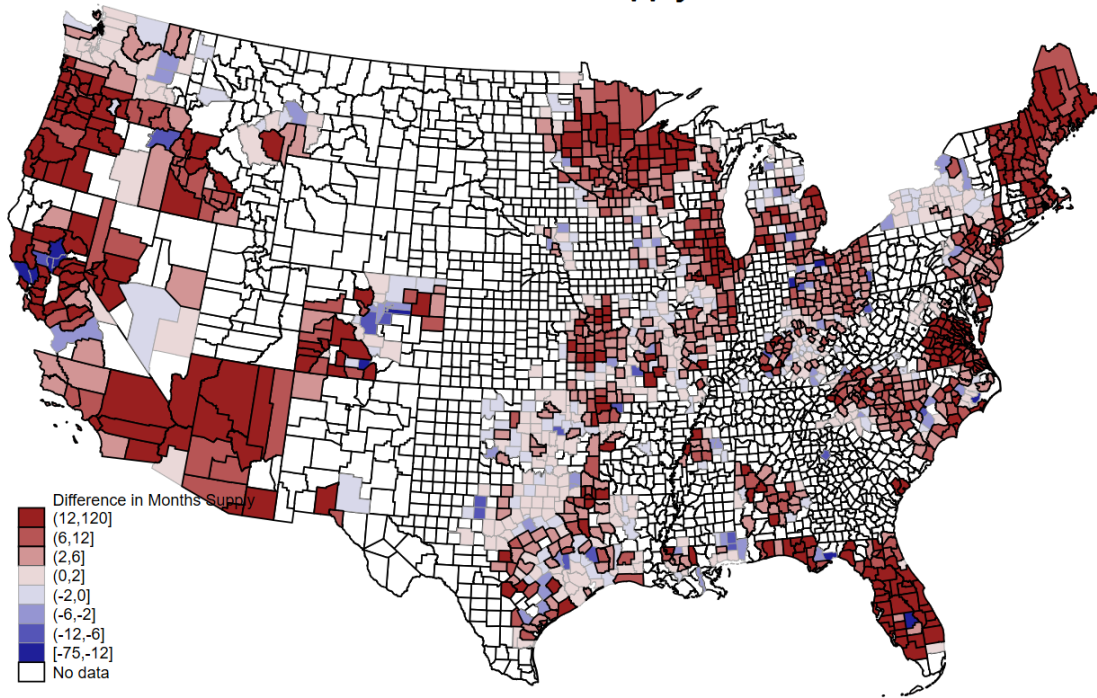


Figure 10: Housing, income, and employment from 2006–2011. Larger circles represent more populous counties. Sources: (Housing) CoreLogic MLS data. (Income) IRS Statistics of Income. (Employment) BLS Quarterly Census of Employment and Wages. Financial variables are deflated by the PCE.

Months of Supply



Time on the Market

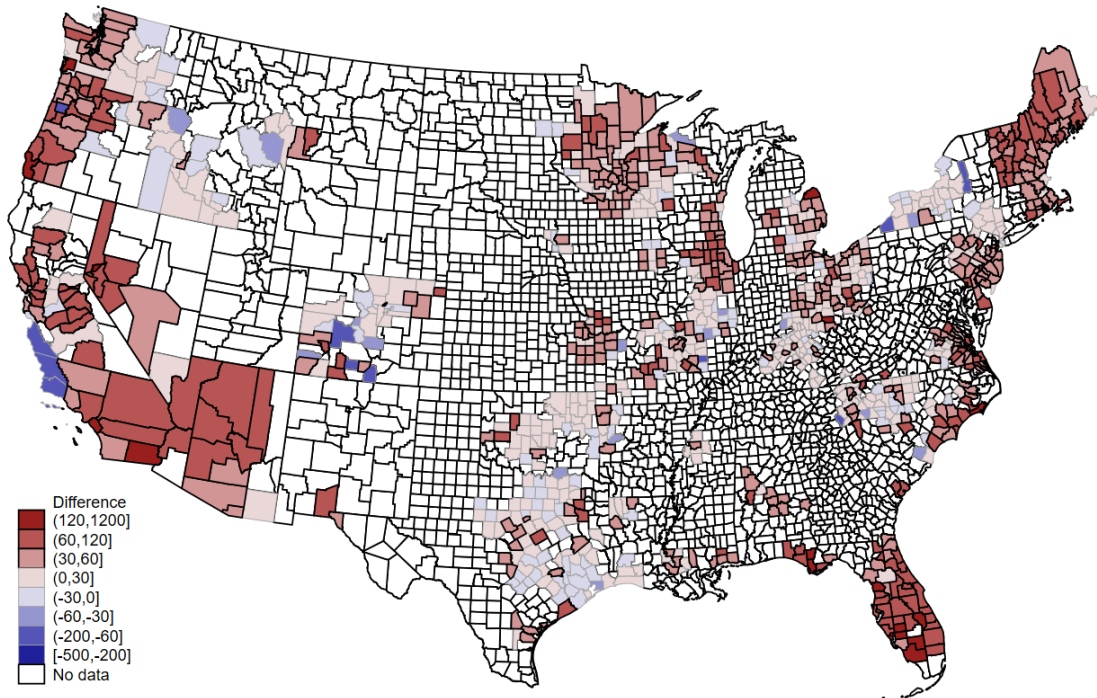


Figure 11: The *change* in months of supply and time on the market (measured in days) from 2005 to 2008. Source: CoreLogic MLS data.

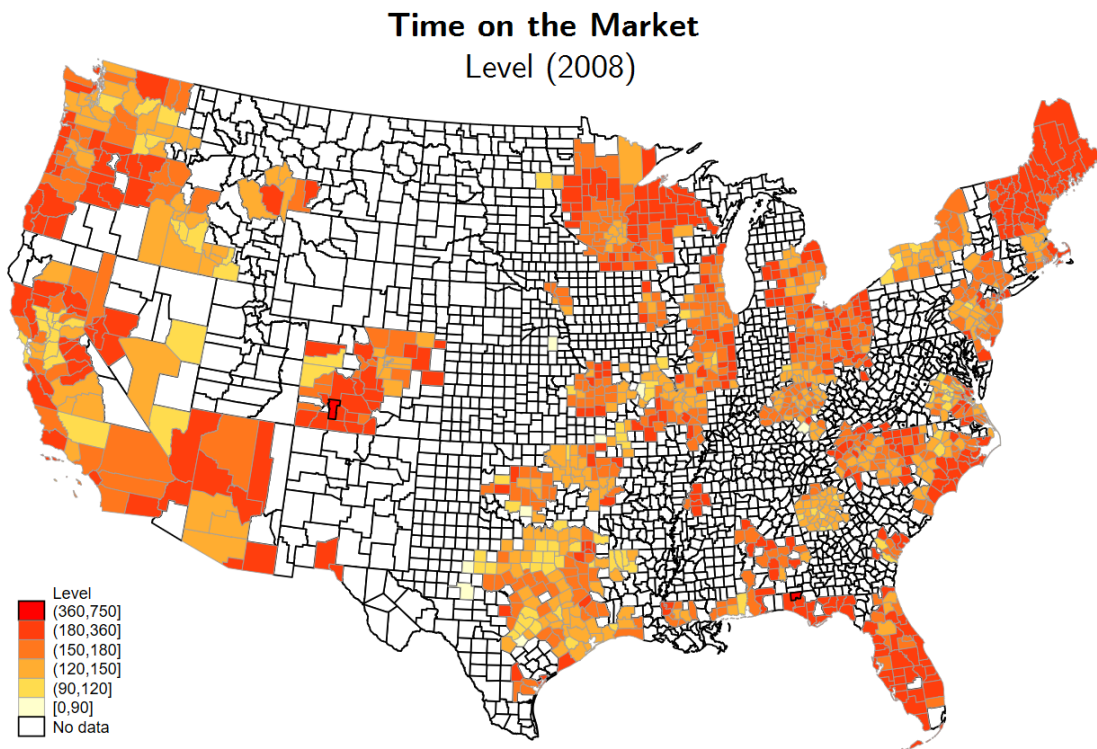
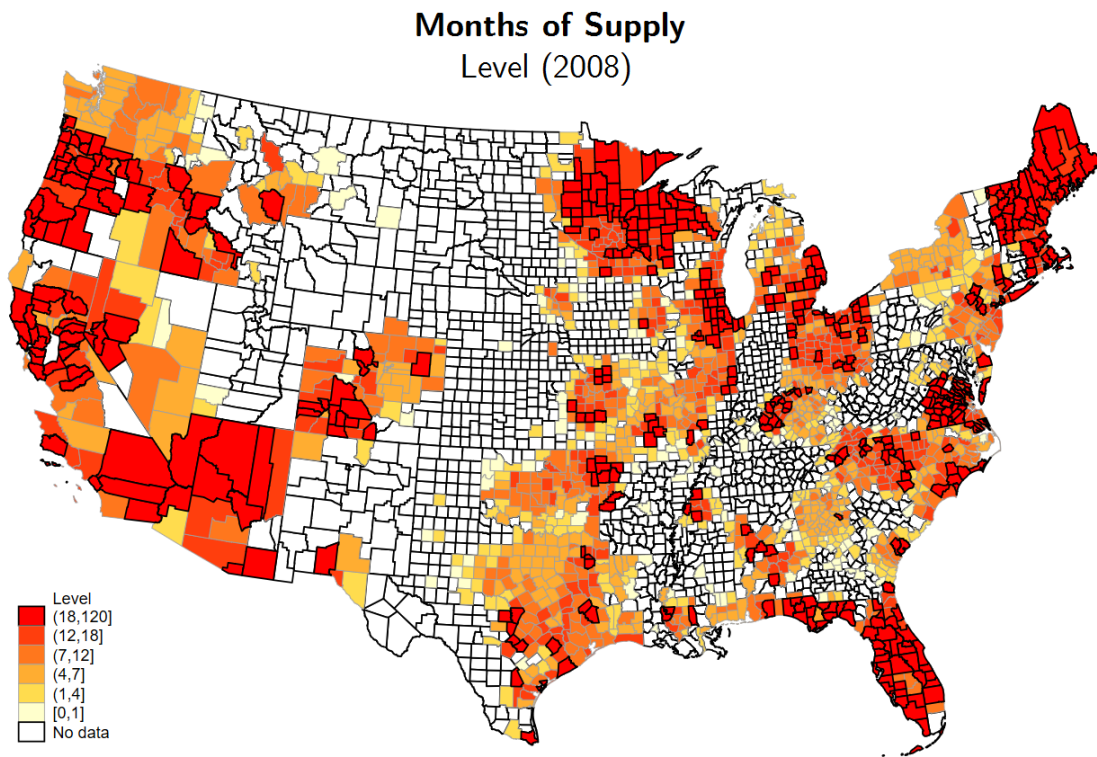
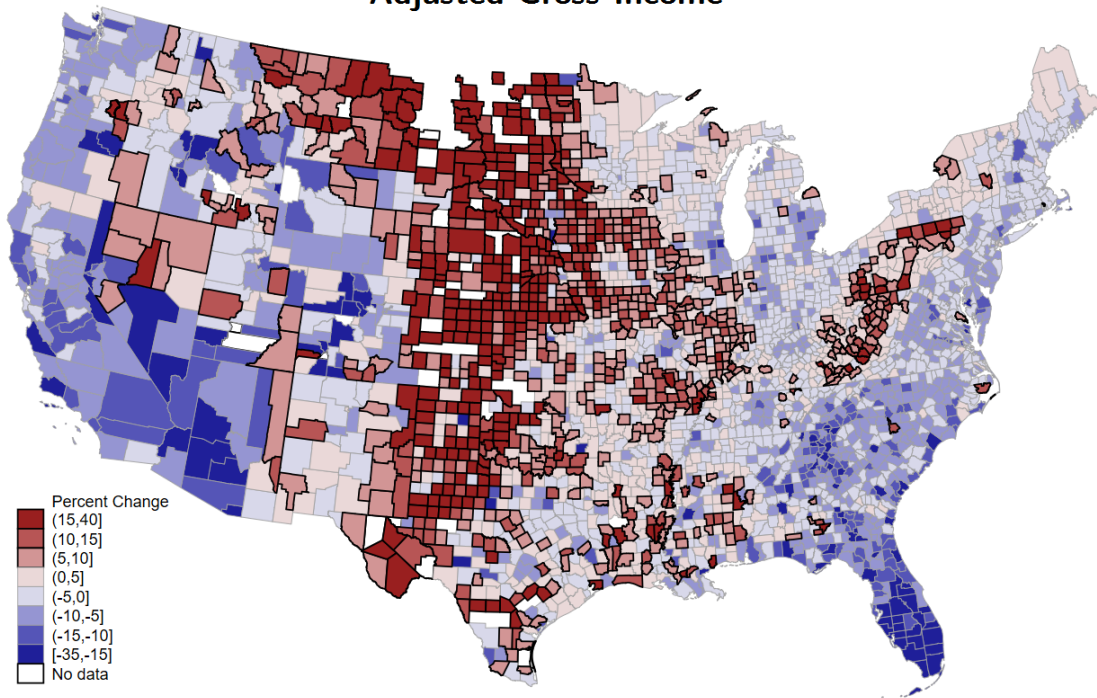


Figure 12: The *level* of months of supply and time on the market (measured in days) in 2008. Source: CoreLogic MLS data.

Adjusted Gross Income



Employment

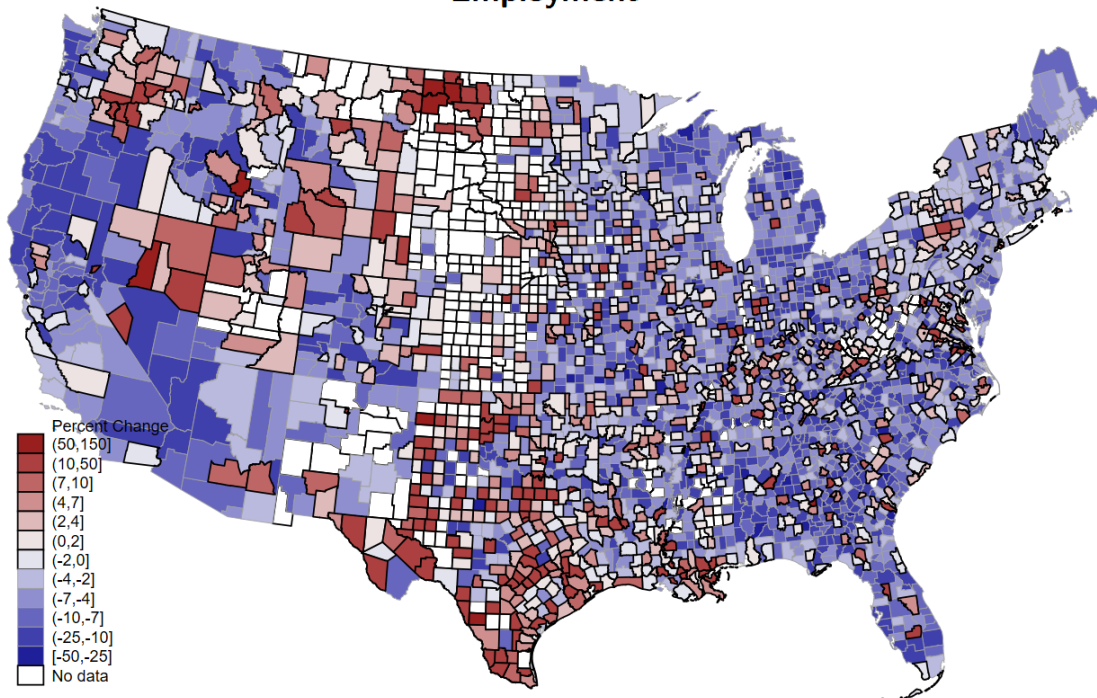


Figure 13: The percentage change in adjusted gross income and employment from 2006 to 2011. Sources: (Income) IRS Statistics of Income. (Employment) BLS Quarterly Census of Employment and Wages.

A.3 Regression Results

This section provides a detailed description of the regressions in section 5 that analyze the transmission from housing to credit and the macroeconomy. Table 12 gives the full regression results corresponding to specification 10, which isolates the impact that changes to house prices and liquidity have on mortgage default at the county level. The positive and statistically significant coefficients for both measures of illiquidity indicate that selling delays are an important contributing factor to default. Given that average county-level months of supply rose by 10.57, the coefficient of 0.125 in table 12 implies an increase in mortgage default of 1.3 percentage points from illiquidity alone.

Table 12: Default and Liquidity

	(1)	(2)
	$\Delta\text{Default}$	$\Delta\text{Default}$
$\% \Delta \text{Prices} \times \frac{H_{06}}{NW_{06}}$	-0.131*** (0.005)	-0.140*** (0.005)
$\Delta \text{Months Supply}$	0.125*** (0.009)	
$\Delta \text{Time on Market}$		0.027*** (0.002)
Constant	0.891*** (0.105)	0.872*** (0.110)
N	1021	935
R^2	0.540	0.545

Regressions are weighted by county population. Default and prices are from 2006 – 2010; months supply and time on the market are from 2005 – 2008. ***Significant at the 1% level.

Table 13 provides estimates for regression specification 13, which measures the macro spillovers—specifically, for adjusted gross income and nontradable employment at the county level—associated with declining house prices and rising illiquidity. Column 1 closely mirrors the main specification in Mian et al. (2013), except that this paper uses a wider time horizon from 2006 to 2011 that covers the entire housing bust instead of only the 2006–2009 period they use. Furthermore, their dependent variable is proprietary Mastercard consumption data instead of the publicly available AGI from the IRS. Even so, the price coefficient of 0.237 is remarkably similar to the 0.341 they obtain for the response of nondurable consumption to house price changes.

Revealing the novel importance of illiquidity, incorporating the lagged change in months of supply from 2005 to 2008 adds a similarly large but negative coefficient while causing the regression to explain a larger share of the AGI variation. For perspective, this coefficient yields a predicted 2 percentage point decline in AGI based on the observed average increase in months of supply during the crisis. Replacing months of supply with time on the market

Table 13: Elasticity to Changes in House Prices and Liquidity

	(1)	(2)	(3)	(4)	(5)	(6)
	% Δ AGI	% Δ AGI	% Δ AGI	% ΔE_{NT}	% ΔE_{NT}	% ΔE_{NT}
% Δ Prices $\times \frac{H_{06}}{NW_{06}}$	0.237*** (0.011)	0.202*** (0.012)	0.229*** (0.012)	0.118*** (0.023)	0.091*** (0.025)	0.090*** (0.026)
Δ Months Supply		-0.188*** (0.022)			-0.143*** (0.047)	
Δ Time on Market			-0.029*** (0.005)			-0.035*** (0.010)
Constant	-1.803*** (0.241)	-0.780*** (0.262)	-0.859*** (0.275)	-0.771 (0.494)	0.010 (0.553)	0.198 (0.575)
N	1023	1023	934	1023	1023	934
R^2	0.304	0.350	0.348	0.025	0.034	0.036

AGI is adjusted gross income; E_{NT} is nontradable employment using the 4-digit NAICS industry classification from [Mian and Sufi \(2014\)](#). Regressions are weighted by county population. Dependent variables and prices are from 2006 – 2011; months supply and time on the market are from 2005 – 2008. ***Significant at the 1% level.

delivers a smaller coefficient, but critically, time on the market is measured in *days* and therefore experiences a much larger increase than does months of supply. A similar back of the envelope calculation based on the average rise in time on the market in [table 11](#) predicts a 1.6 percentage point drop in AGI.

Switching from AGI to nontradable employment as the macro variable of interest as in [Mian and Sufi \(2014\)](#) changes the coefficients but not the underlying message. In particular, the price coefficient of 0.118 in the regression without illiquidity is close to the 0.190 estimate they obtain, even though the time horizon in this paper is 2006–2011 instead of 2007–2009. As in the case of AGI, introducing either months of supply or time on the market reveals an economically meaningful and statistically significant effect of illiquidity. Specifically, the regression predicts a 1.9 percentage point decline in nontradable employment based on the observed rise in time on the market.

Lastly, [table 14](#) shows the results for [specification 14](#) in [section 5.3.1](#) that measures the marginal impact of house price and liquidity changes on county-level income. If AGI is viewed as a proxy for consumption, the house price coefficient of 0.03 in the regression without illiquidity is in line with the 0.047 and 0.054 empirical estimates for the marginal propensity to consume out of house price changes in [Aladangady \(2017\)](#) and [Mian et al. \(2013\)](#), respectively. Put another way, the regression predicts a \$30 fall in AGI in response to a \$1,000 decline in house prices. Showing again the macroeconomic importance of illiquidity, [column 2](#) reveals that each additional month of supply is associated with a \$89 drop in AGI, and each one *day* increase in time on the market predicts a \$31 fall in AGI, which corresponds to a \$1,700 total effect based on the observed rise in time on the market in the data.

Table 14: Marginal Response of Income to Prices and Liquidity

	(1)	(2)	(3)
	Δ AGI	Δ AGI	Δ AGI
Δ Prices	0.030***	0.027***	0.033***
Δ Months Supply		-89.264*** (17.412)	
Δ Time on Market			-31.282*** (3.520)
Constant	-1262.632*** (165.868)	-766.795*** (190.267)	-3.910 (202.868)
N	1023	1023	934
R^2	0.343	0.359	0.412

Regressions are weighted by county population. AGI and prices are from 2006 – 2011; months supply and time on the market are from 2005 – 2008. ***Significant at the 1% level.

B Supplementary Tables and Figures

This appendix provides companion figures and tables regarding model fit, transmission mechanisms, and alternative explanations for the housing crisis.

B.1 Additional Dimensions of Model Fit

Section 5 discusses at length the importance of balance sheet depth during the crisis. In particular, illiquidity-induced debt overhang for households with high initial leverage causes a pronounced increase in foreclosure risk, a contraction in the supply of credit, and a larger drop in house prices and consumption. Thus, it is important that the pre-crisis parametrization properly capture the right tail of the mortgage leverage distribution that acts as the source for many of the model nonlinearities. Figure 14 shows that, indeed, the parametrized model does remarkably well at matching this important segment of the leverage distribution from the 2007 Survey of Consumer Finances while also replicating the targeted aggregate portfolio statistics in table 1.

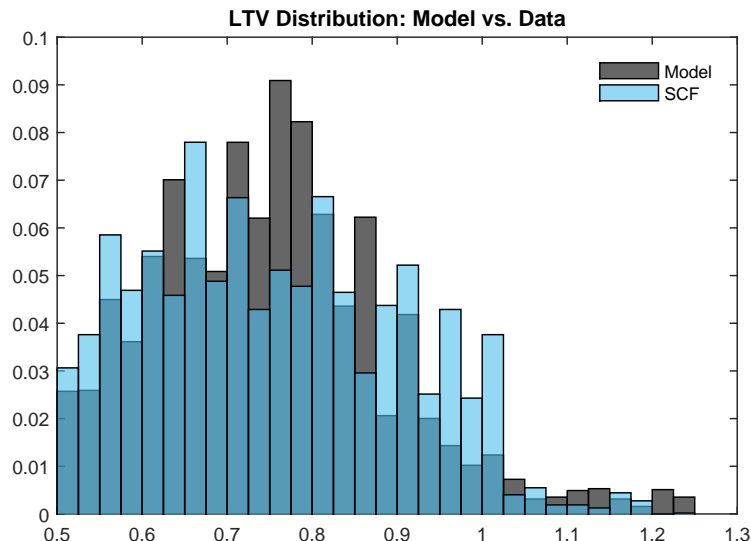


Figure 14: Pre-bust LTV distribution in the model and in the 2007 SCF.

B.1.1 Selected Shocks in the Model and Data

Figure 15 depicts the skewness and interest rate shocks from the model next to their empirical counterparts. Although households in the model inelastically supply *raw* labor, their individual effective labor supply $e_t \cdot z_t$ is stochastic. As explained in section 4, the skewness shocks are implemented as temporary changes to the transition matrix π_z . First, downside risk in π_z is increased for 3 years to match the decline in aggregate employment from the BLS over that same horizon. Then, a reversal in downside risk is implemented to match the pace of the employment recovery. Finally, π_z is reset to its pre-crisis state. The left panel shows the behavior of aggregate labor in the model and data.

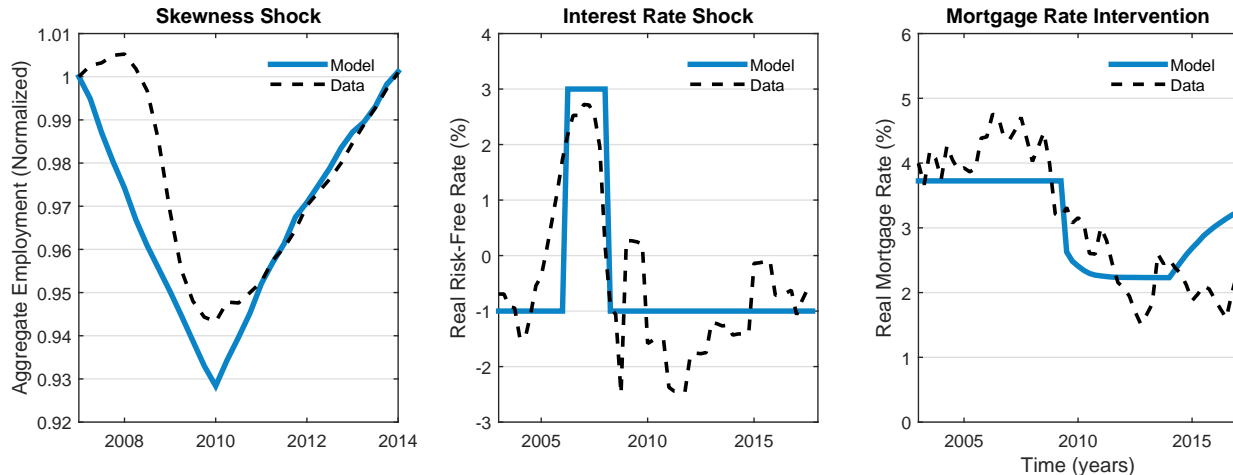


Figure 15: Select shocks in the model and data. (Left) Aggregate employment. (Middle) Real risk-free rate. (Right) Real mortgage rate. The decline in panel 3 corresponds to nominal mortgage rates falling from around 5.5% to 4%.

The middle panel shows the dynamics of the risk-free rate i_t . In the model, i_t is exogenously increased (because of the open economy assumption) for two years to approximate the tightening in monetary policy during 2006 and 2007 and then lowered again to reflect the Federal Reserve’s reversal as the economy began to collapse. Despite this temporary increase in i_t , long-term mortgage rates r_t —which are set according to equation 30—do *not* rise, as seen in the right panel.⁵⁰ Instead, they initially remain flat and subsequently fall after policy interventions were enacted to reduce long-term borrowing costs. In the model, lower mortgage rates are instituted via reduced servicing costs ϕ_t .

B.1.2 Further Cross-Validation

The open economy assumption in the model implies that net financial flows—measured as the gap between total financial (i.e. liquid) assets and mortgage debt—are typically non-zero. Although the model parametrization targets several aggregate and cross-sectional portfolio statistics from the 2007 Survey of Consumer Finances, it does not target the pre-crisis size of this net financial position. Nevertheless, the initial gap between the two curves in figure 16 shows that the model closely mirrors the data.

During the crisis, net financial flows increase (become less negative) in the data and in the model, as seen both in the left panel for levels and in the right panel, which measures the *change* in these flows. These dynamics emerge from a combination of higher savings and lower debt. The temporary rise in the risk-free rate increases the return to saving, and heightened downside risk strengthens households’ precautionary motive to save. The reduction in mortgage debt comes about because of higher mortgage outflows from foreclosures and reduced inflows from changes both on the demand and supply side. In particular, the increased riskiness of housing reduces the appeal of homeownership, and the contraction in credit—which occurs both because of the exogenous credit limit shocks and

⁵⁰Recall that endogenous default risk is incorporated in mortgage *prices* q_t at origination.

the endogenous rise in default spreads—reduces the ability of buyers to finance purchases through borrowing. In addition to matching these net financial flows, the model generates aggregate foreclosure losses amounting to 12.6% of annual goods output, which is in line with the magnitude of losses reported by the IMF.⁵¹

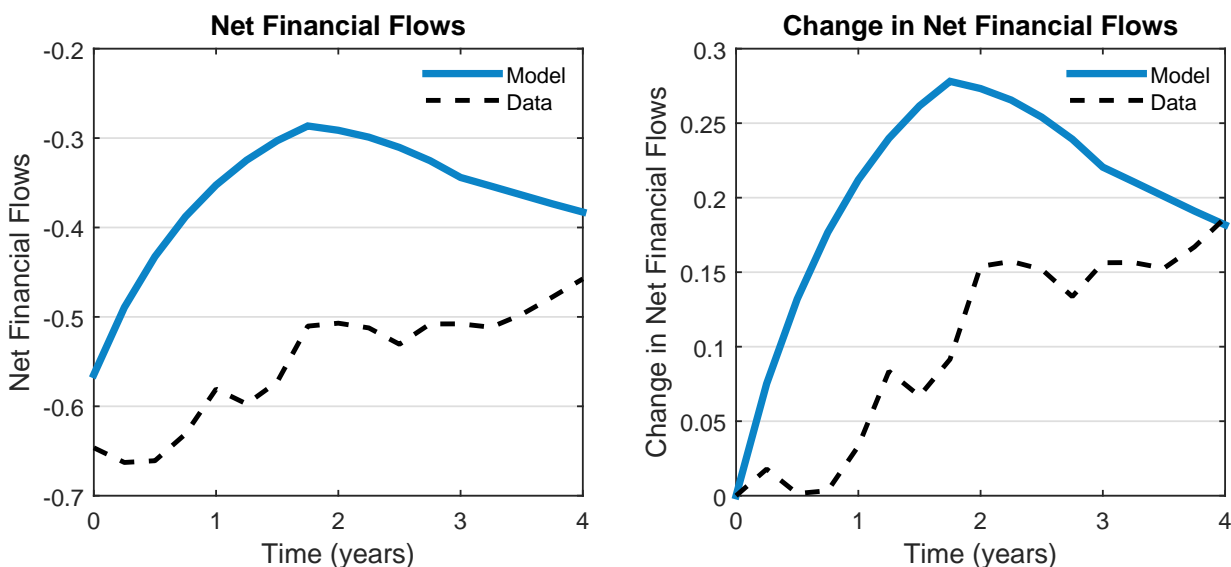


Figure 16: (Left) Net financial flows in the model and data. (Right) Dynamics after subtracting the pre-crisis gap between model and data. Net flows in the data are from the Flow of Funds and are defined as total financial deposits (FL154000025Q) minus the sum of mortgage debt (FL153165105Q) and consumer credit (FL153166000Q). This measure is deflated by the PCE and normalized by total annual earnings from the Bureau of Economic Analysis.

Figure 17 complements tables 3, 6, and 7 in section 5 that show the model’s success in matching the aggregate and cross-sectional behavior of consumption during the crisis. The top left panel shows that aggregate consumption in the model and data falls by approximately 10%, while the remaining three panels reveal the significant degree of heterogeneity in consumption dynamics by net worth, tenure status, and degree of leverage. In particular, heavily-indebted owners experience the largest decline in consumption followed by less leveraged owners and, finally, renters. These patterns reinforce the discussion in section 5.3.2 about the importance of balance sheet depth.

⁵¹See <https://www.nytimes.com/2009/04/22/business/global/22fund.html>.

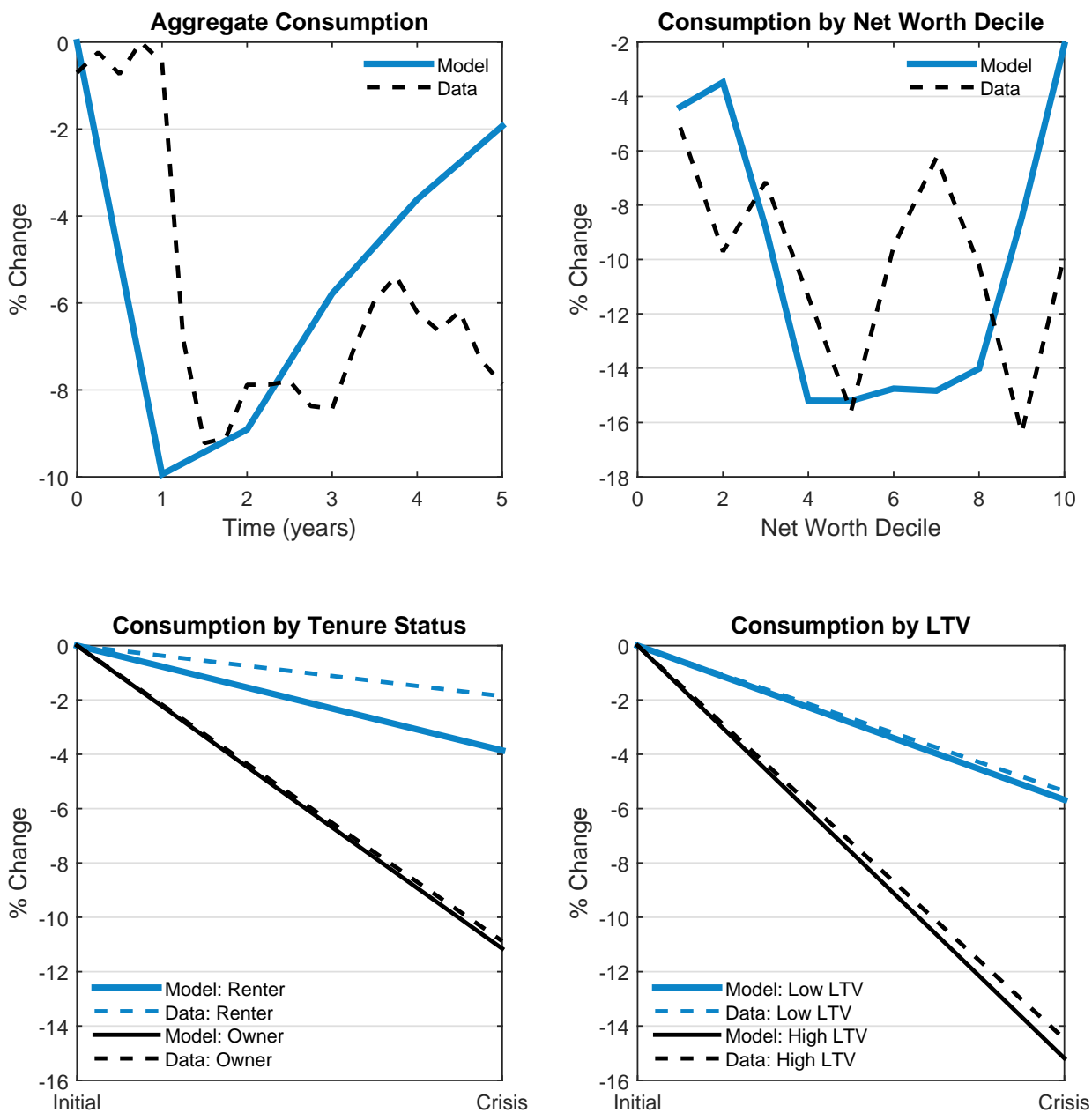


Figure 17: Sources: (Aggregate) BEA nondurable consumption deflated by the PCE (detrended from extrapolated 1991 – 2000 linear trend). (Disaggregated) PSID using the sampling criteria of Arellano et al. (2017). Low loan-to-value (LTV) is below 0.3; high LTV is above 0.8.

B.2 Housing Behavior in the Cross Section

This section adds to section 5.1.1 by analyzing the cross-sectional behavior of foreclosures, homeownership, and the liquidity-adjusted double trigger.

B.2.1 Default, Tenure Flows, and the “New Narrative”

Two of the most salient features of the 2006–2011 housing crisis were the wave of mortgage defaults and the associated persistent homeownership decline. Challenging the view that these maladies were concentrated in the subprime market, several recent empirical papers have used administrative credit panel data to uncover evidence pointing to the broad-based nature of the foreclosure crisis.⁵² The cross-sectional model results in the top row of figure 18 are consistent with this new narrative. In particular, foreclosures spike both in the bottom and middle segments of the market, with only high-income borrowers at the top end of the market emerging relatively unscathed. Turning to the top right panel, *relative* gross exits into renter status are initially most pronounced among owners of medium-sized houses whose deeper balance sheets and higher leverage make them more financially exposed to shocks. Over time, the collateral damage from tighter credit limits and increased downside earnings risk also takes its toll on owners of small houses as they transition out of owning and into renting. In *absolute* terms, the equilibrium house size distribution *conditional on ownership* remains relatively stable, although the staggered timing of exits from owning to renting—first for medium houses, and then for small houses—is evident in the bottom left panel. Lastly, the bottom right panel shows the decline in the aggregate housing stock as depressed construction fails to keep up with depreciation.

B.2.2 The Liquidity-Adjusted Double Trigger

As a supplement to section 5.2.1, figures 19 and 20 provide a visual depiction of mortgage default with and without endogenous housing liquidity. The height of the “mountain peak” at each point corresponds to the measure of homeowners with that combination of mortgage leverage and cash at hand at the time of the house price trough, while the shading indicates each household’s foreclosure propensity, with brighter colors representing higher default risk. In the top panel of figure 19, low-income borrowers with negative equity (leverage above 1) default with near certainty, which is consistent with the standard double trigger. However, some borrowers with modest amounts of *positive* equity but little cash at hand *also* default with strictly positive probability because of selling delays from debt overhang, which is indicative of the **liquidity-adjusted double trigger**. By contrast, the bottom panel shows the stark “bang-bang” nature of default in the standard double trigger: for given cash at hand, the probability of foreclosure immediately jumps from 0 to 1 upon passing some leverage threshold.

The same differences between the standard and liquidity-adjusted double triggers appear for middle-income homeowners in figure 20, which also sheds light on the broad-based nature of the foreclosure crisis. Even though middle-income borrowers have lower default

⁵²See, for example, Adelino, Schoar and Severino (2016), Foote, Loewenstein and Willen (2016), and Albanesi, DeGiorgi and Nosal (2017).

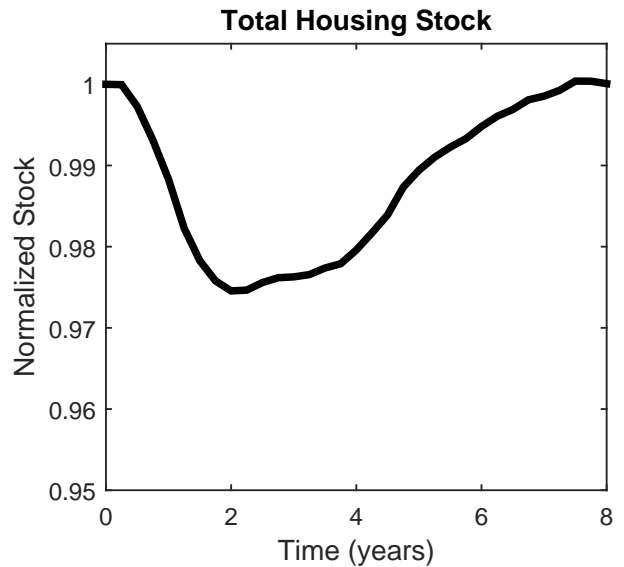
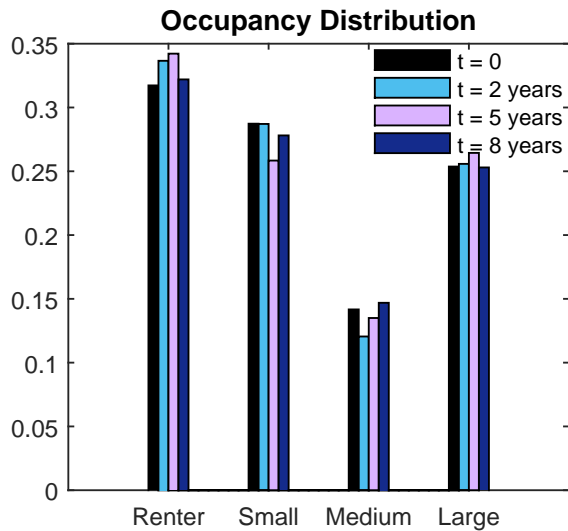
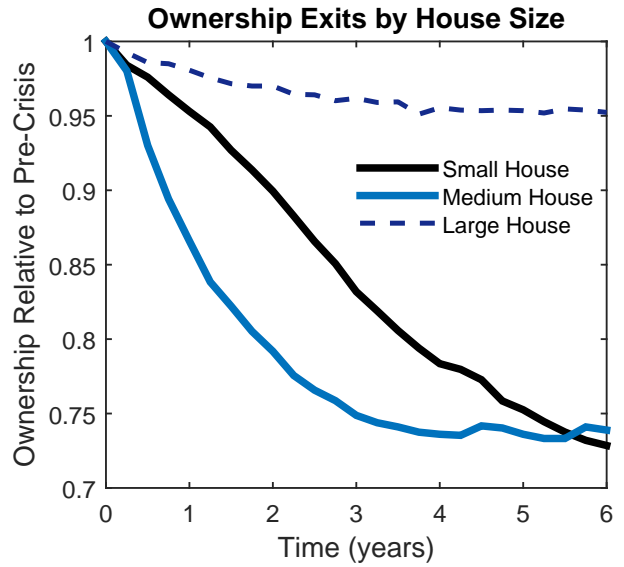
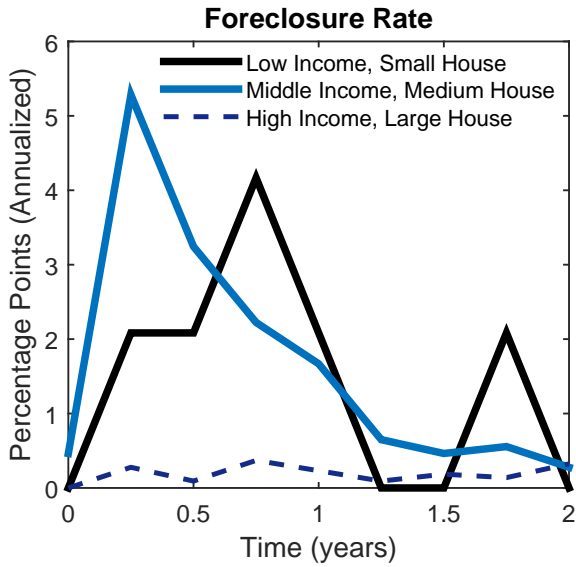


Figure 18: (Top Left) Foreclosure rate by pre-crisis income state and house size. (Top Right) Ownership rate by pre-crisis house size. (Bottom Left) Distribution of occupancy across renter status and house sizes. (Bottom Right) The dynamics of the aggregate housing stock, $H_t = (1 - \delta_h)H_{t-1} + Y_{ht}$.

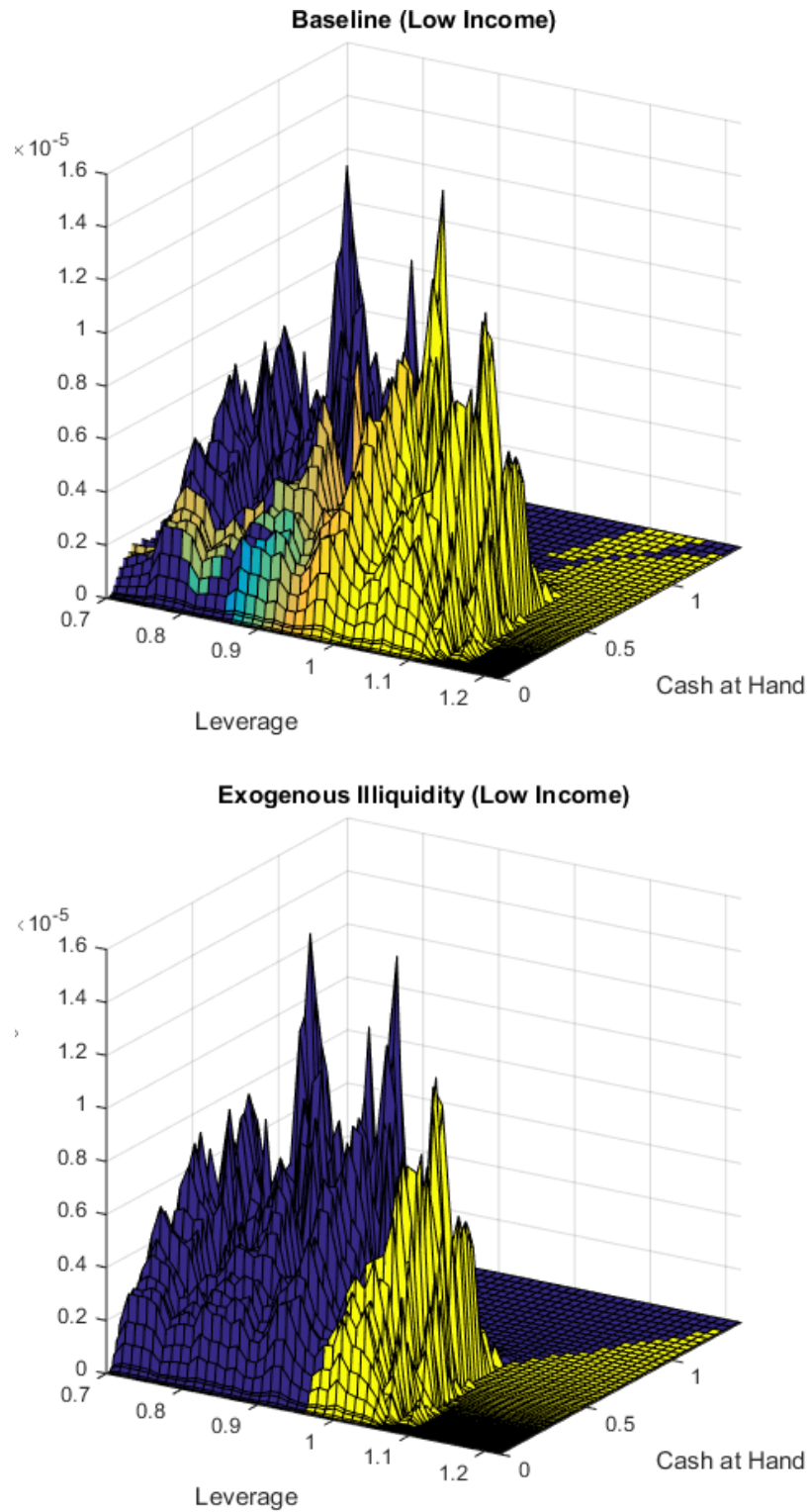


Figure 19: Distribution of low-income households in the bust with lighter shading indicating higher default probabilities. Foreclosures at lower LTV values in the baseline are driven by illiquidity-induced failures to sell.

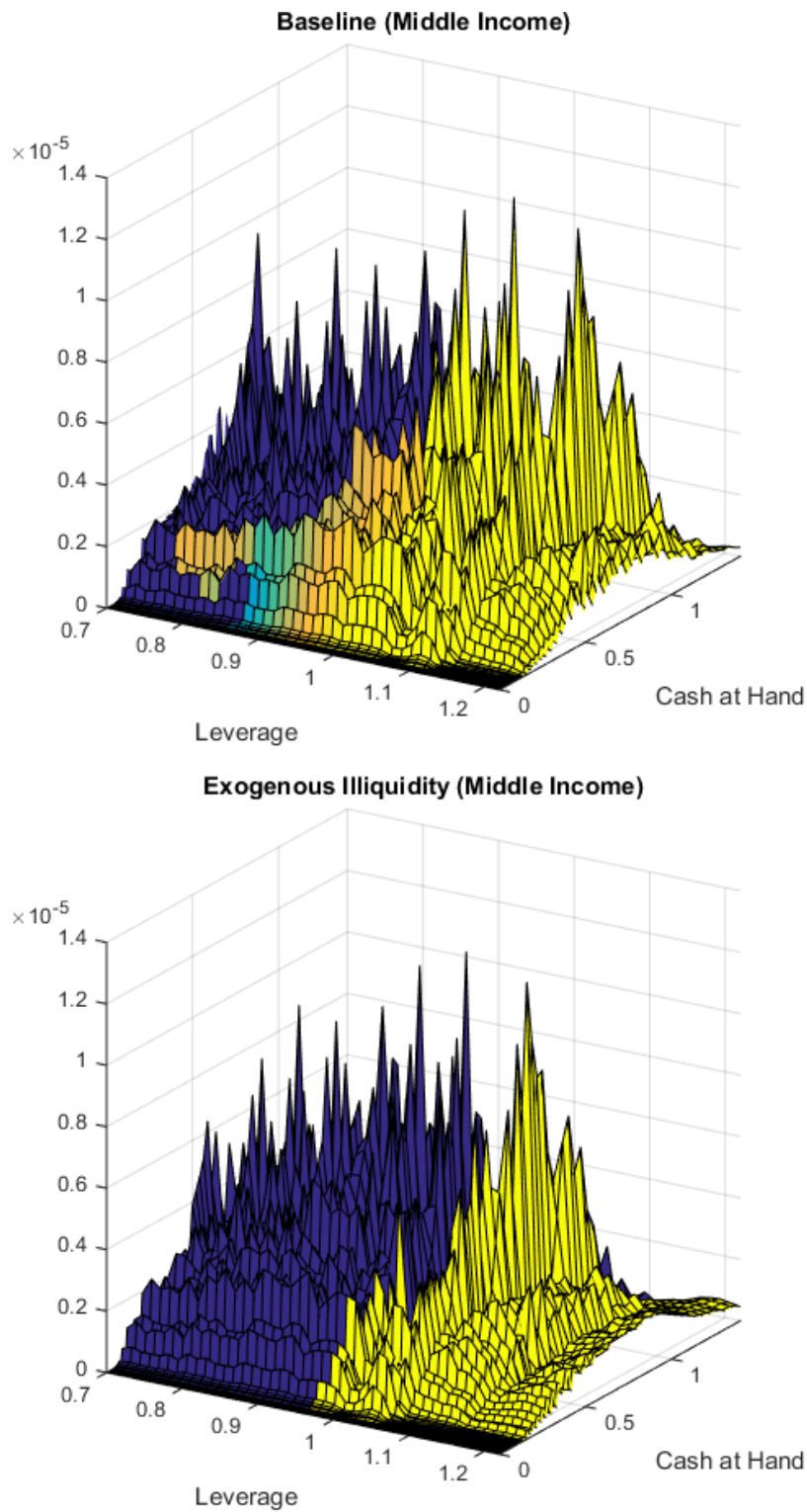


Figure 20: Distribution of middle-income households in the bust with lighter shading indicating higher default probabilities. Foreclosures at lower LTV values in the baseline are driven by illiquidity-induced failures to sell.

propensities than *otherwise identical* low-income borrowers with the same leverage and cash at hand, there is a *greater mass* of highly leveraged middle-income borrowers because their lower foreclosure risk grants them better access to credit at a reduced premium. Thus, middle-income borrowers contribute just as much to the total foreclosure rate during crises because they disproportionately inhabit a risky portion of the state space that exposes them to deteriorating housing market conditions.

B.2.3 Construction, Reshuffling, and the Occupancy Distribution

As in most workhorse macro-housing models, the construction of new housing is akin to the production of new capital—that is, housing is built in continuous and divisible units. It is only when households buy and sell houses that they are restricted to transacting indivisible house sizes from a discrete set. The conventional approach used in frictionless models assumes that the Walrasian auctioneer can costlessly reshuffle the housing stock across the discrete house sizes and clears the market at a uniform per-unit housing price. In this model, the real estate brokers provide a similar function, which leads to analogous (though not identical) equilibrium conditions. Proceeding in this manner gives rise to one equilibrium price (or price index) p_t as opposed to a vector of equilibrium prices $\{p_t(h)\}_h$ corresponding to each house size. To make the comparison between the Walrasian auctioneer and real estate brokers more evident, the Walrasian equilibrium condition (without foreclosures, for simplicity) is

$$\underbrace{\int h_t^* \mathbf{1}_{[buy_t^*]} d\Phi_t^{rent}}_{\mathcal{D}_t(p_t)} = Y_{ht}(p_t) + \underbrace{\int h \mathbf{1}_{[sell_t^*]} d\Phi_t^{own}}_{\mathcal{S}_t(p_t)},$$

where the indicator function on the left is the decision of whether to buy a house or not, and h_t^* is the choice of house size (with the dependence of these policy functions on p_t and state variables suppressed here). On the right-hand side, Y_{ht} is the construction of new housing given by the builder’s standard first order conditions described in section C, and the second term is the total volume of housing sold by owners aggregated across house sizes, where the indicator function is the binary decision of whether to sell or not.

With directed search and brokers, the analogous equilibrium condition is

$$\int h_t^* \eta^{buy}(p_t^{bid*}, h_t^*; p_t) d\Phi_t^{rent} = Y_{ht}(p_t) + \int h \eta^{sell}(p_t^{list*}, h; p_t) d\Phi_t^{own}.$$

The main difference between these two equations is that, with search, only successful transactions (i.e. not failed searches) appear on either side. In the Walrasian model, all it takes is for a buyer or seller to decide they want to transact, which flips the indicator function from 0 to 1. By contrast, with search frictions, sellers (buyers) of house h choose a list price p_t^{list*} (bid price p_t^{bid*}) and succeed with probability $\eta^{sell}(p_t^{list*}, h; p_t)$ ($\eta^{buy}(p_t^{bid*}, h; p_t)$).

Although the equilibrium conditions with and without search frictions resemble each other, the baseline model actually does better at avoiding reshuffling between house sizes. Figure 21 provides a direct comparison of the amount of reshuffling in the baseline and Walrasian models. In the baseline model, there are only slight changes in the distribution of house sizes over time, whereas the Walrasian model shows larger amounts of reshuffling.

Specifically, in the Walrasian model, there is a significant decline in the number of small houses between $t = 2$ and $t = 5$ accompanied by a spike in the number of medium-sized houses during this period as buyers take advantage of cheap prices. By contrast, the increased difficulty of selling in the model with search-induced endogenous liquidity significantly attenuates this opportunistic upgrading during bad times.

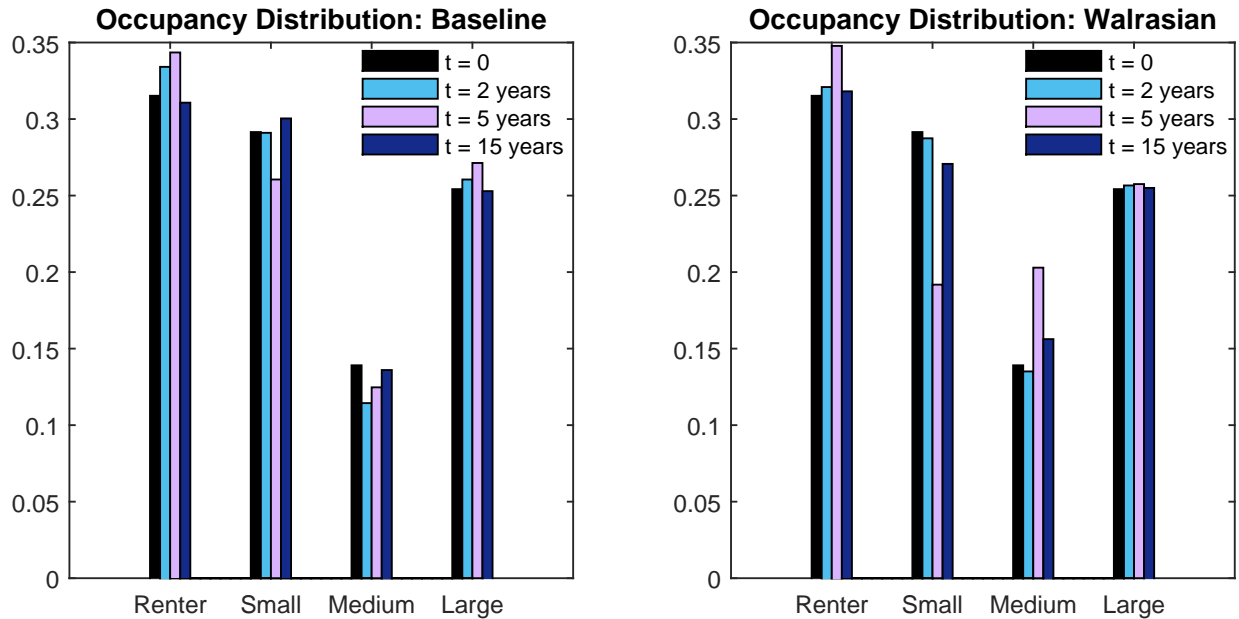


Figure 21: Dynamics of the occupancy distribution across house sizes in the baseline (left) and Walrasian (right) economies.

Table 15: Quantifying the Drivers of the Housing Bust

	Baseline	Exclude*	Alone**	Impact Bounds
<i>Skewness Shock</i>				
Δ House Prices	-23.4%	-14.8%	-11.6%	[-11.6%, -8.6%]
Δ Ownership	-2.8pp	+1.2pp	-3.1pp	[-4.0pp, -3.1pp]
Δ Months Supply	+6.5m	+3.0m	+1.3m	[+1.3m, +3.5m]
Δ Foreclosures	+5.1pp	+1.1pp	+0.2pp	[+0.2pp, +4.0pp]
Δ Consumption	-9.9%	-6.3%	-2.8%	[-3.6%, -2.8%]
<i>Credit Shock</i>				
Δ House Prices	-23.4%	-19.1%	-5.6%	[-5.6%, -4.3%]
Δ Ownership	-2.8pp	-3.0pp	+0.9pp	[+0.2pp, +0.9pp]
Δ Months Supply	+6.5m	+3.5m	+0.3m	[+0.3m, +3.0m]
Δ Foreclosures	+5.1pp	+2.3pp	-0.2pp	[-0.2pp, +2.8pp]
Δ Consumption	-9.9%	-7.0%	-2.2%	[-2.9%, -2.2%]
<i>Productivity Shock</i>				
Δ House Prices	-23.4%	-21.6%	-1.9%	[-1.9%, -1.8%]
Δ Ownership	-2.8pp	-2.9pp	+0.7pp	[+0.1pp, +0.7pp]
Δ Months Supply	+6.5m	+5.5m	+0.5m	[+0.5m, +1.0m]
Δ Foreclosures	+5.1pp	+3.6pp	-0.4pp	[-0.4pp, +1.5pp]
Δ Consumption	-9.9%	-8.0%	-1.0%	[-1.9%, -1.0%]
<i>Interest Rate Shock</i>				
Δ House Prices	-23.4%	-20.2%	-3.7%	[-3.7%, -3.2%]
Δ Ownership	-2.8pp	-2.9pp	+0.5pp	[+0.1pp, +0.5pp]
Δ Months Supply	+6.5m	+4.8m	+0.5m	[+0.5m, +1.7m]
Δ Foreclosures	+5.1pp	+4.4pp	-0.4pp	[-0.4pp, +0.7pp]
Δ Consumption	-9.9%	-8.7%	-2.0%	[-2.0%, -1.2%]

*The shock's effect in this case is the difference between the "baseline" and "exclude" columns. **The other shocks are removed.

B.3 Decomposing the Housing Bust

Section 5.1 focuses on the role of worse earnings skewness and tighter credit limits as drivers of the housing crash. This section goes further by fully decomposing—visually and quantitatively—the contributions of all the productivity, interest rate, skewness, and credit limit shocks. Figure 22 shows the marginal impact of each shock. The curves prefaced with “no” remove the shock, and the “only” curves remove the other three shocks instead. The skewness and credit shocks have the largest impact on house prices, consumption, and foreclosures. Critically, the skewness shock is necessary to explain the decline in homeownership. Table 15 quantifies these effects.

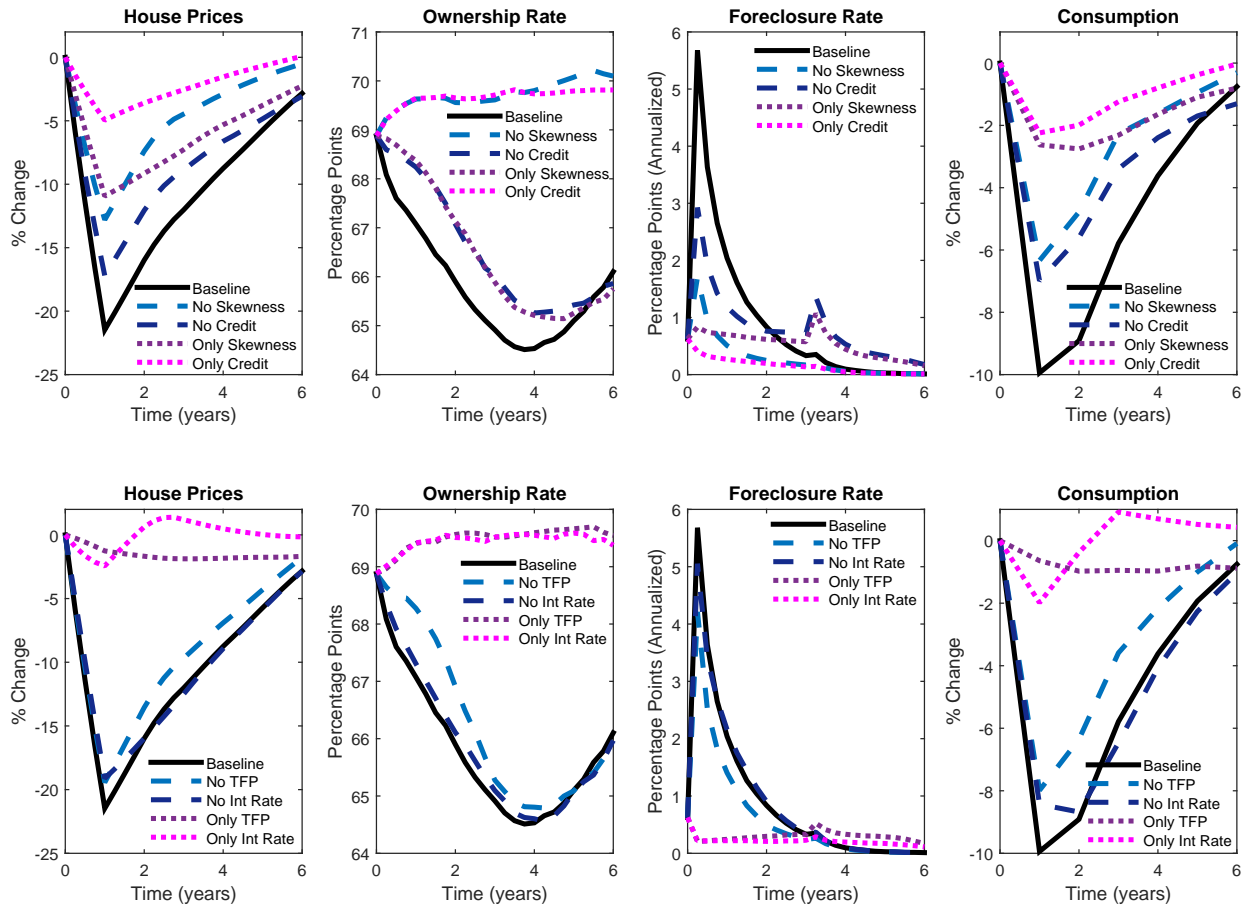


Figure 22: (Top) Decomposing the skewness and credit shocks. (Bottom) Decomposing the productivity and interest rate shocks. Plots with “No” remove the shock; plots with “Only” remove the *other* shocks.

B.3.1 Skewness Shocks: Realizations vs. Uncertainty

Figure 23 decomposes the effect of skewness shocks into earnings realizations vs. higher downside uncertainty. To isolate the effect of worse realizations, the model is simulated under the assumption that households do not perceive the change in their transition matrix π_z . The second simulation flips this scenario by removing the skewness shocks without the households' knowledge, leading them to false believe downside earnings risk is higher. Figure 23 also shows the baseline model and the version without skewness shocks entirely. Consistent with recent work by Berger et al. (2019), worse realizations have the largest negative impact, although uncertainty noticeably amplifies the response of sales, foreclosures, and consumption while also depressing homeownership.

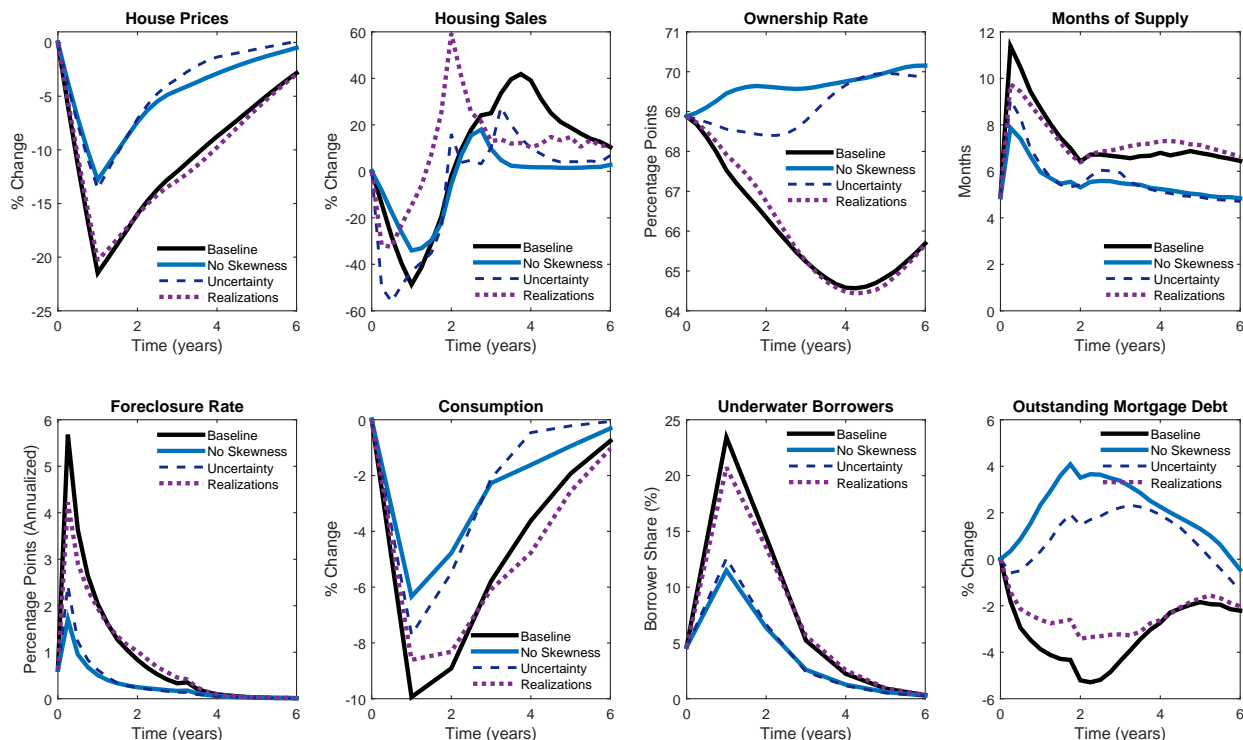


Figure 23: Decomposing the role of realizations vs. uncertainty from skewness shocks. “Uncertainty” captures just the effect of households’ *belief* that skewness has worsened. The “Realizations” curve shows the impact of worse skewness when households are naively unaware of the change in earnings risk. The “No Skewness” plot shuts off skewness shocks entirely.

B.3.2 The Distributional Effects of Skewness and Credit Shocks

Complementing the discussion in section 5.1.2, figures 24 and 25 show the cross-sectional implications of skewness and credit limit shocks for consumption. The top row in each figure plots slices of average consumption over time by tenure, leverage, and financial distress status, and the bottom row shows the entire distribution of the peak-to-trough decline in consumption for each of these groups. In figure 24, removing the skewness shock provides significant relief to distressed owners, who no longer face the pressure to severely cut consumption in response to higher downside earnings risk. In figure 25, the removal of the credit limit shock relaxes homeowners' ability to extract equity through refinancing, which mitigates the consumption decline especially for highly leveraged and distressed owners.

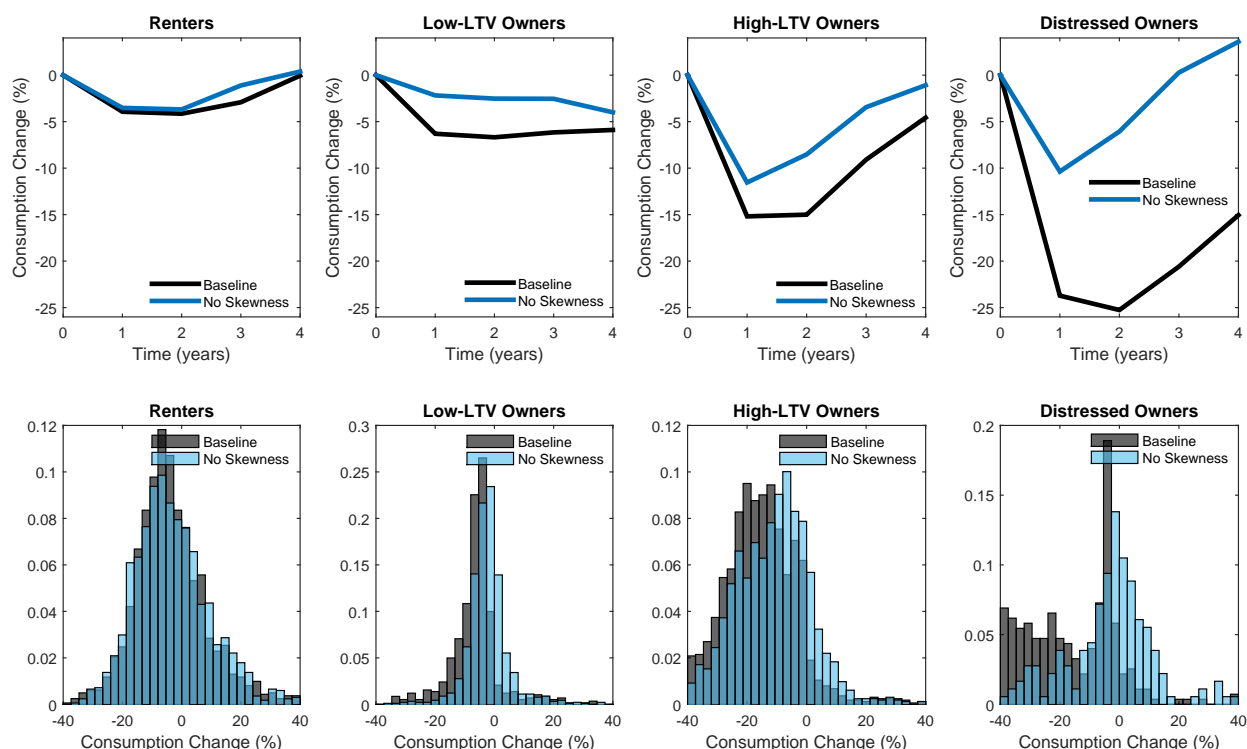


Figure 24: The consumption effects of removing skewness shocks. Low loan-to-value (LTV) is below 0.3; high LTV is above 0.8. Distressed owners are those who default 1 year *after* the beginning of the Great Recession.

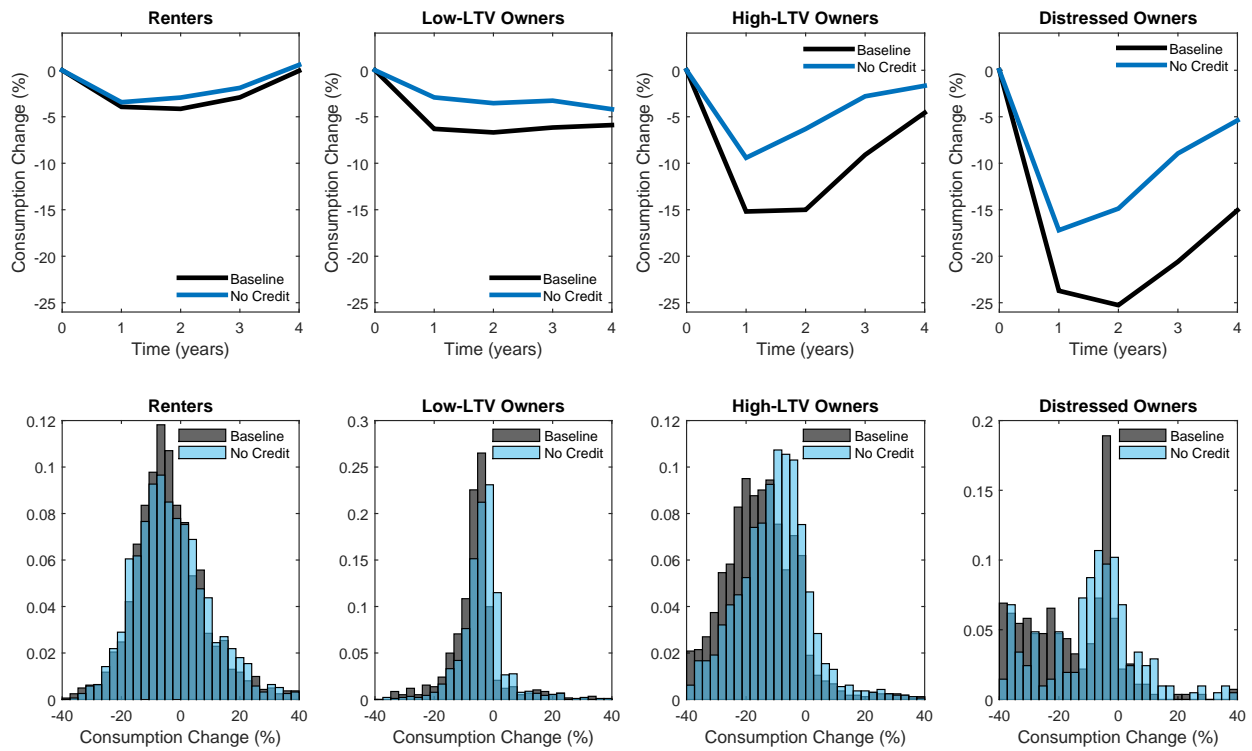


Figure 25: The consumption effects of removing credit shocks. Low loan-to-value (LTV) is below 0.3; high LTV is above 0.8. Distressed owners are those who default 1 year *after* the beginning of the Great Recession.

B.4 Robustness

This section explores the implications of altering either the timing or duration of the shocks that are summarized by the timeline in figure 26.

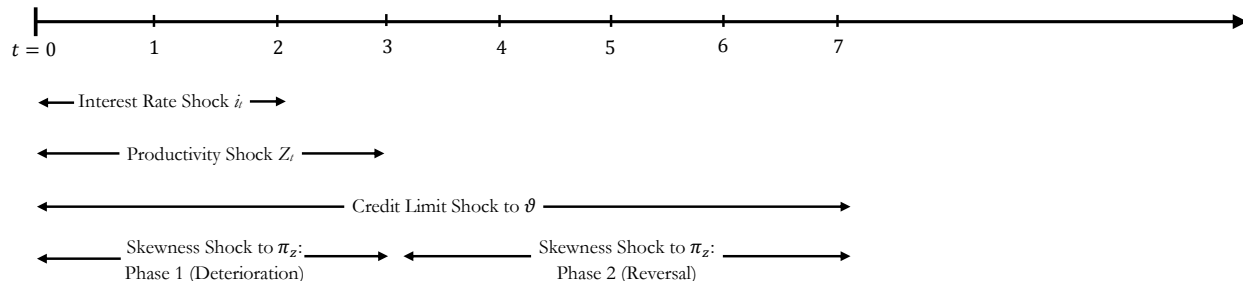


Figure 26: Shock timeline in the baseline.

B.4.1 Staggering the Arrival of Shocks

In the baseline implementation, all of the shocks arrive simultaneously. As a robustness test, this section subjects the economy to two waves of shocks. First, the unanticipated credit shocks arrive. Then, agents are surprised again one year later by the arrival of the skewness and productivity shocks. Figure 27 summarizes this staggered timeline.

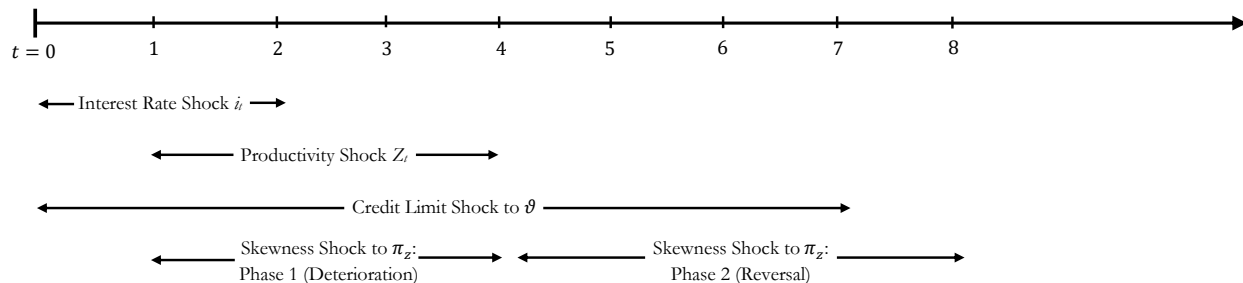


Figure 27: Staggered arrival of shocks.

As figure 28 makes evident, the dynamics of house prices and foreclosures are largely unchanged when the earnings and productivity shocks arrive with a delay. The staggered timing causes a slightly smaller deterioration in both variables, but it also produces more persistence. The delayed ownership decline in the middle panel reinforces the discussion in section 5.1.2 that highlights the critical role of the skewness shocks in depressing ownership.

B.4.2 Forward-Looking Behavior and Terminal Conditions

Even though each of the following experiments only involves changing the *end date* of the shocks, terminal conditions affect economic dynamics during the entire transition path because of forward-looking behavior by households and lenders. Going from the most extreme to the least extreme case, extending the shocks to credit limits, interest rates,

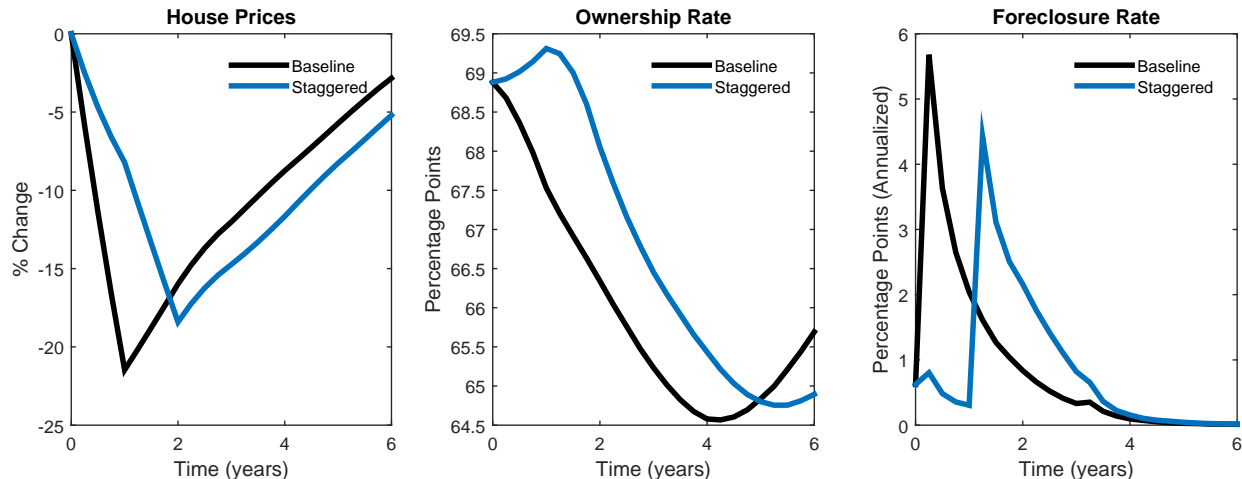


Figure 28: Results with a delayed arrival of skewness and productivity shocks.

and productivity indefinitely—which means a permanent 5% decline in wages, real risk-free rates of 3% instead of -1% (with higher mortgage rates as a result), and a permanent 10% minimum down payment requirement—causes a severe deepening of the housing crisis. House prices fall twice as far, the consumption decline is amplified by 60%, and the foreclosure rate peaks at 18% as nearly two-thirds of homeowners find themselves underwater (i.e. owing more on their mortgage than their house is worth). In addition, the stock of outstanding mortgage debt drops substantially. Needless to say, these results show the importance of future expectations about terminal conditions, but the simulated time series in this case are a dramatic exaggeration of what occurred in the data. Making only the credit limit and interest rate shocks permanent by allowing productivity to recover acts as an intermediate point between the baseline and the previous case, but the large, permanent decline in outstanding debt is at odds with the data. Lastly, making only the tighter down payment constraint permanent causes the trajectory of the economy to differ only modestly from the baseline path. However, a permanent 10% minimum down payment requirement is at odds with the return of low-LTV lending in recent years.

B.4.3 Alternative Drivers

Section 5.1.2 affirms the role of credit as a driver of housing market behavior while also establishing the novel importance of downside uncertainty during the Great Recession. Although for this paper the elevated uncertainty in the model comes through higher left tail earnings risk from skewness shocks, a large body of recent empirical literature highlights the importance of uncertainty, broadly conceived, during the crisis.⁵³ For robustness, this

⁵³See Shoag and Veuger (2016), Arellano, Bai and Kehoe (2019), Stock and Watson (2012), and Bloom et al. (2018) for an analysis of uncertainty in the Great Recession. In addition, Jurado, Ludvigson and Ng (2015) identify 2007–2009 as “the most striking period of heightened uncertainty since 1960,” and Berger et al. (2019) emphasize the importance of left-skewed shocks for matching the relationship between uncertainty and the macroeconomy. Kozeniauskas, Orlik and Veldkamp (2018) provide a unified discussion of how to define and measure uncertainty.

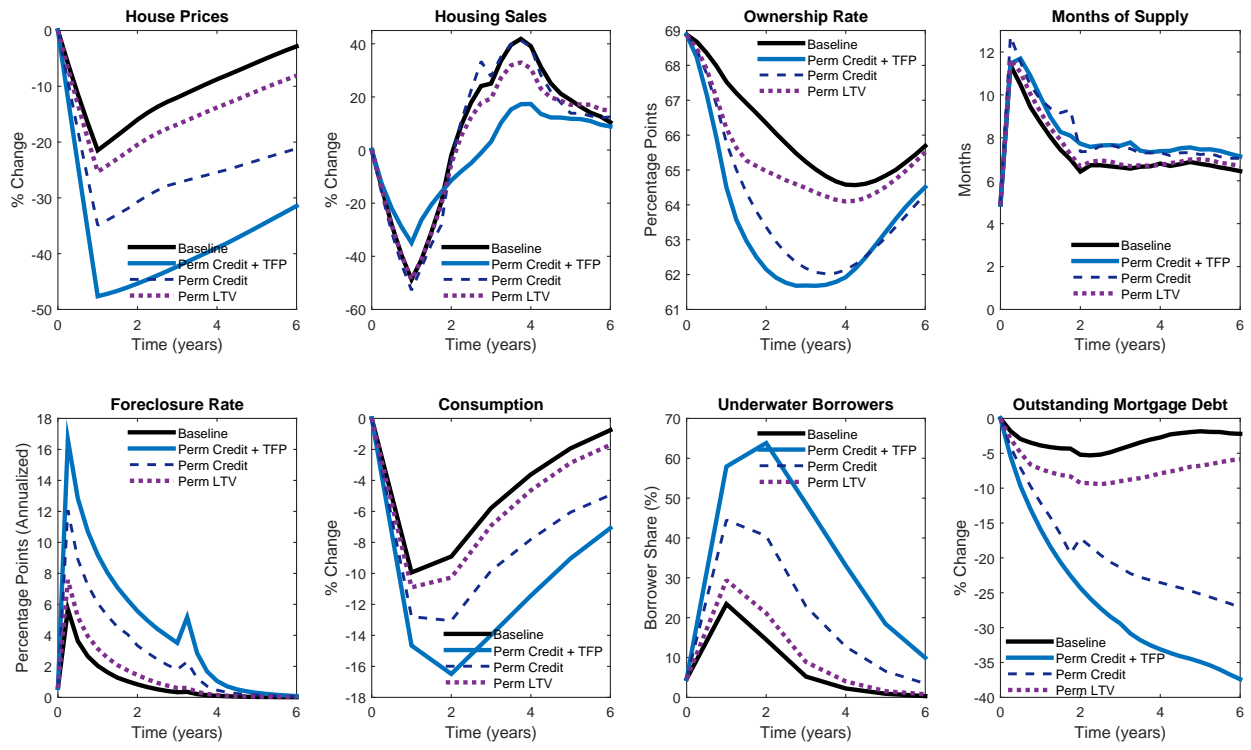


Figure 29: The effect of making shocks permanent. “Perm Credit + TFP” makes the credit, interest rate, and TFP shocks permanent, but the skewness shocks remain temporary. “Perm Credit” makes only the credit and interest rate shocks permanent (i.e. the real risk-free rate goes to 3% in the long run). “Perm LTV” makes only the tighter down payment constraint permanent.

section evaluates a selection of possible alternative drivers of the housing crash involving housing preference shocks, housing belief shocks, and unusually large productivity shocks.

Housing Preference Shocks Figure 30 shows the economic response to an *immediate, permanent* shock to preferences (specifically, a hike in the consumption weight ω) that reduces agents’ taste for housing. The “pref shock only” curve shows the equilibrium path with *only* this shock, and the dashed line shows the combined effect of this preference shock together with the interest rate, credit limit, and productivity shocks from the baseline—that is, when the skewness shock is replaced with the preference shock. It is immediately evident from the counterfactual increase in consumption that the preference shock cannot be the only driving force behind the Great Recession. Furthermore, even though agents have a lower preference for housing, the decline in prices causes ownership and mortgage debt to counterfactually *rise*.

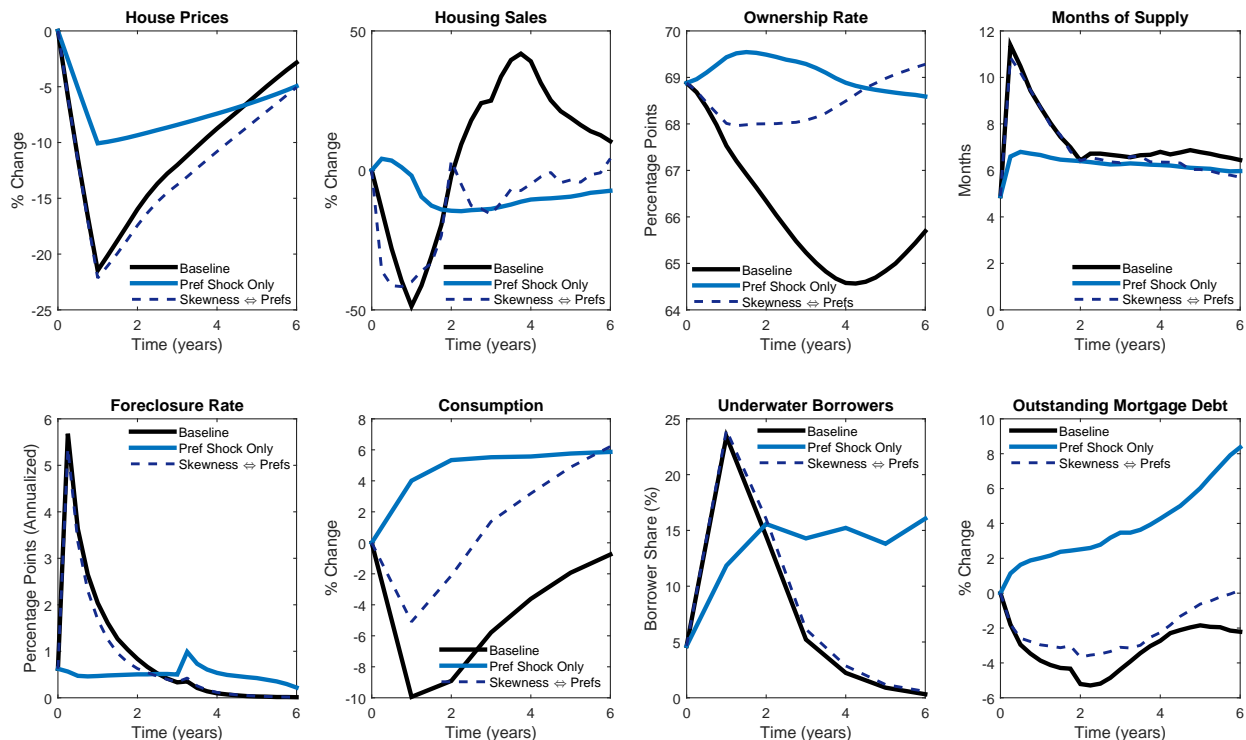


Figure 30: The effect of housing preference shocks. “Pref Shock Only” includes an *immediate, permanent* negative shock to the preference for housing as the only shock. “Skewness ⇔ Prefs” retains the credit, productivity, and interest rate shocks from the baseline but swaps out the skewness shock with the housing preference shock.

The addition of the interest rate, credit limit, and productivity shocks reverses this counterfactual consumption boom, but even so, the decline is too shallow and short-lived, and low-LTV owners still experience a counterfactual rise in consumption, as observed in figure 31. Moreover, homeownership barely budes instead of experiencing the deep decline observed in the data.

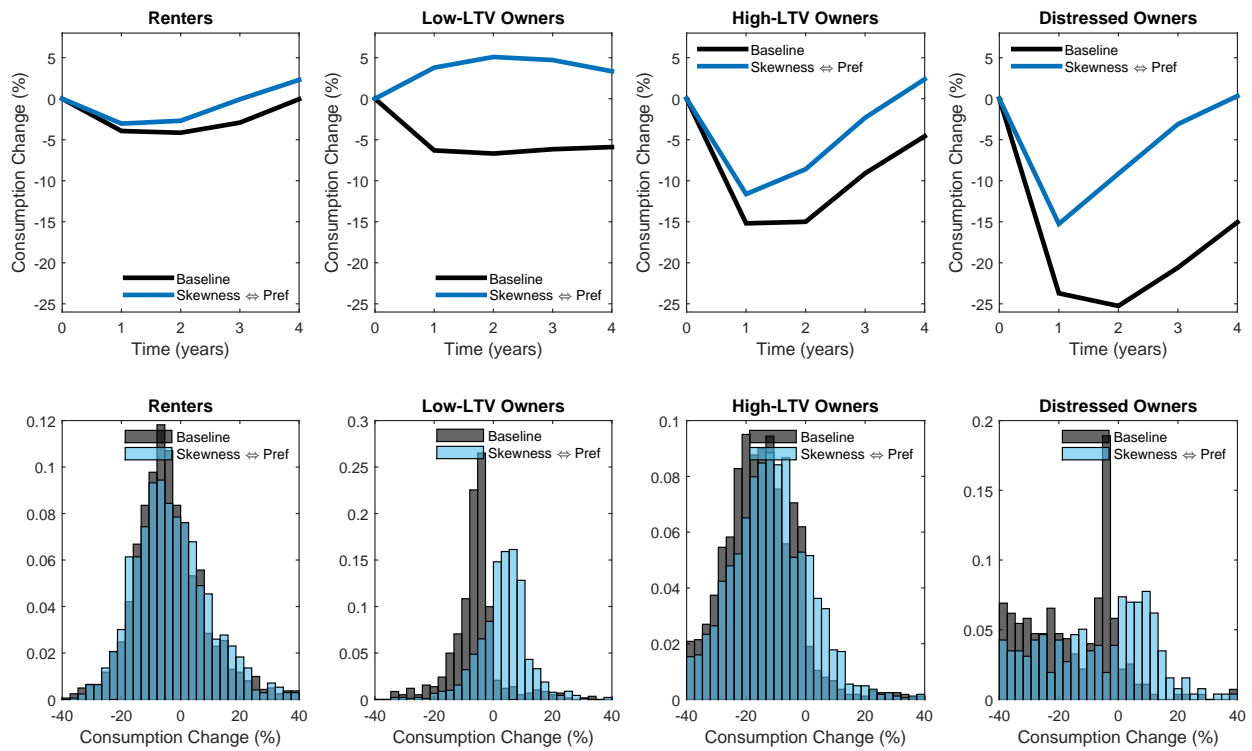


Figure 31: The distributional impact of swapping the skewness shock for a negative shock to housing preferences. Low loan-to-value (LTV) is below 0.3; high LTV is above 0.8. Distressed owners are those who default 1 year *after* the beginning of the Great Recession.

Pessimistic Housing Beliefs Kaplan et al. (2019) resolve the counterfactual negative co-movement between house prices and consumption induced by preference shocks during a simulated boom-bust episode by instead shocking households' *beliefs* about the likelihood of a *future* change in the taste for housing. Furthermore, to prevent these counterfactual dynamics from simply materializing later, Kaplan et al. (2019) then assume that the preference shock never actually materializes. Nevertheless, households still react immediately based on their (ex-ante rational, but ex-post false) beliefs about the future. Figure 32 shows the results of an analogous experiment in this model which announces to agents that there will be a *future, permanent* preference shock that decreases the taste for housing starting at $t = 3$. Regardless of whether the shock actually occurs (as in the figure) or unexpectedly never materializes (which would imply surprising households again at $t = 3$), the endogenous economic response between $t = 0$ and $t = 3$ to agents' pessimistic housing beliefs is the same.

Figure 32 shows that, if the anticipated future preference shock is large enough, it can induce a significant decline in house prices but still only a modest rise in foreclosures and drop in consumption. Moreover, the belief shock produces almost no change in homeownership, even if combined with the interest rate, credit limit, and productivity shocks, and yet still manages to generate excessive deleveraging as pessimistic homeowners unload mortgage debt from their balance sheets. This behavior conflicts with the empirical evidence in Bhutta (2015), which attributes most of the modest decline in outstanding mortgage debt to reduced inflows caused by a “dramatic falloff in first-time homebuying.”

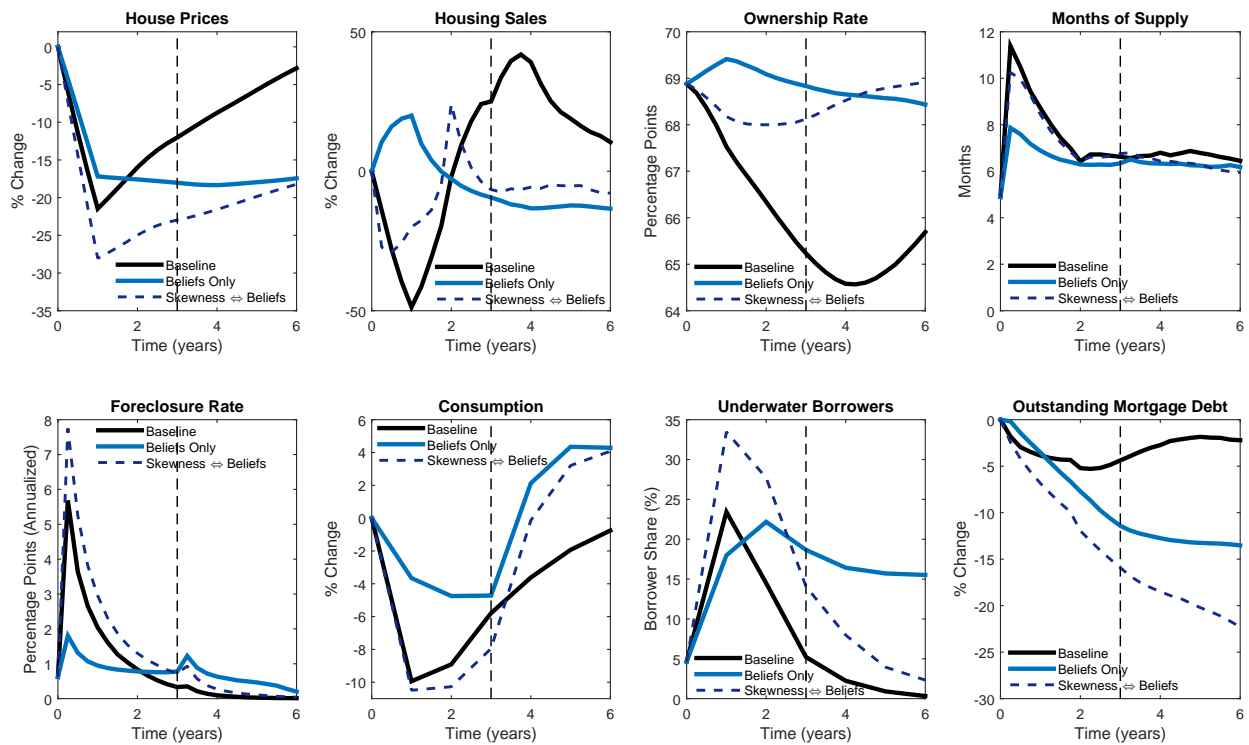


Figure 32: The effect of housing pessimism. “Beliefs Only” introduces a *future, permanent, and fully anticipated* negative shock to the preference for housing as the only shock. “Skewness ⇔ Beliefs” retains the credit, productivity, and interest rate shocks from the baseline but swaps out the skewness shock with the housing pessimism shock.

Productivity Disasters and Earnings Pessimism Section 5 finds that the baseline 5% productivity shock contributes only modestly to the housing crash. By contrast, the skewness shock has large effects. On the surface, both types of shocks reduce aggregate earnings. However, they differ profoundly in other ways. Specifically, the productivity shock reduces earnings deterministically, immediately, and uniformly for all households. By contrast, the skewness shock causes earnings to fall *stochastically, gradually, and unevenly*. Thus, relative to productivity shocks, the deterioration in skewness concentrates bad earnings realizations among the lower and middle class while simultaneously creating a sense of *earnings pessimism* that induces precautionary behavior—most notably the desire to avoid the consumption commitment of homeownership until housing becomes more liquid and less risky.

To isolate the effect of earnings pessimism from the uneven incidence of lower earnings realizations—and to test for nonlinearities in the response of housing and consumption to aggregate earnings—the baseline skewness shocks to π_z are replaced with a sequence of across-the-board shocks to effective labor supply $e_t \cdot z_t$ that produce the same path of aggregate labor shown in figure 15. Notably, the combination of the original productivity shock with these labor shocks is isomorphic to a “productivity disaster” consisting of a gradual deterioration and recovery in aggregate productivity that bottoms out at just over a 10% decline, which is similar to Glover, Heathcote, Krueger and Ríos-Rull (2019). Thus, to simplify exposition, this experiment analyzes the impact of a productivity disaster working in conjunction with the interest rate and credit limit shocks. Importantly, because households perceive that productivity will continue to fall for multiple years, they have pessimism about future earnings. However, unlike with skewness shocks, households in this case know with certainty that they will all equally bear the burden of the aggregate earnings reduction.

Figure 33 shows that, even in this productivity disaster scenario, the deterioration in house prices, foreclosures, and consumption is noticeably smaller than in the baseline. Furthermore, the familiar counterfactual rise in homeownership and mortgage debt re-emerges. Thus, combining the insights of this experiment with the uncertainty vs. realizations decomposition in section B.3.1 reveals that the skewness shocks play such an important role as a driver of the housing crash because of the trifecta of higher uncertainty, worse pessimism, and an uneven incidence of the aggregate earnings decline across households felt most saliently at the bottom and middle of the income distribution.

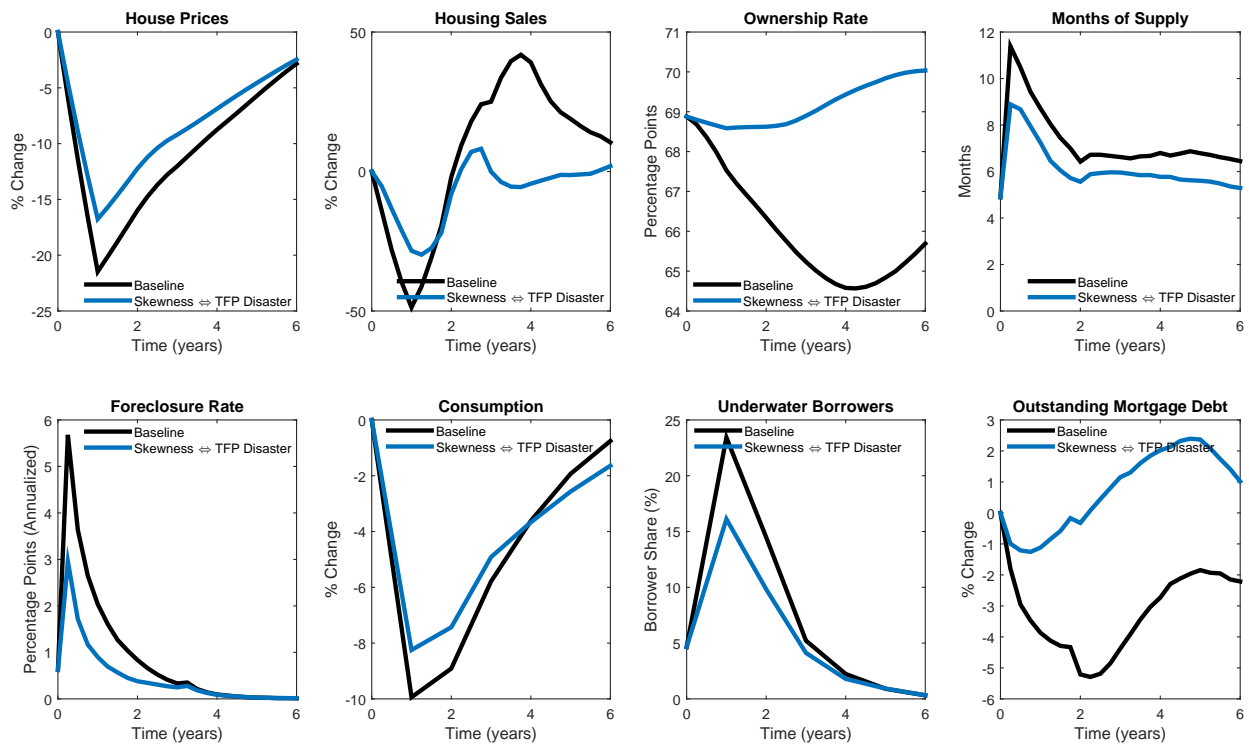


Figure 33: Replacing skewness shocks with a “productivity disaster” that combines the original productivity shock with a sequence of across-the-board shocks to effective labor supply that produces the same path of aggregate labor as does the skewness shocks.

B.5 Housing Spillovers to Consumption

This section provides supplemental information regarding the transmission of house prices to consumption through the balance sheet.

B.5.1 Aggregate Nonlinearities and Shock Dependence

Section 5.3 mentions that the elasticity of consumption to house prices is not a single invariant number. Instead, the transmission from housing to consumption is dynamic and shock-dependent. Figures 34 and 35 provide a visual illustration of this point by taking turns either removing or introducing each shock one at a time, just as in the decompositions from section 5.1.2.

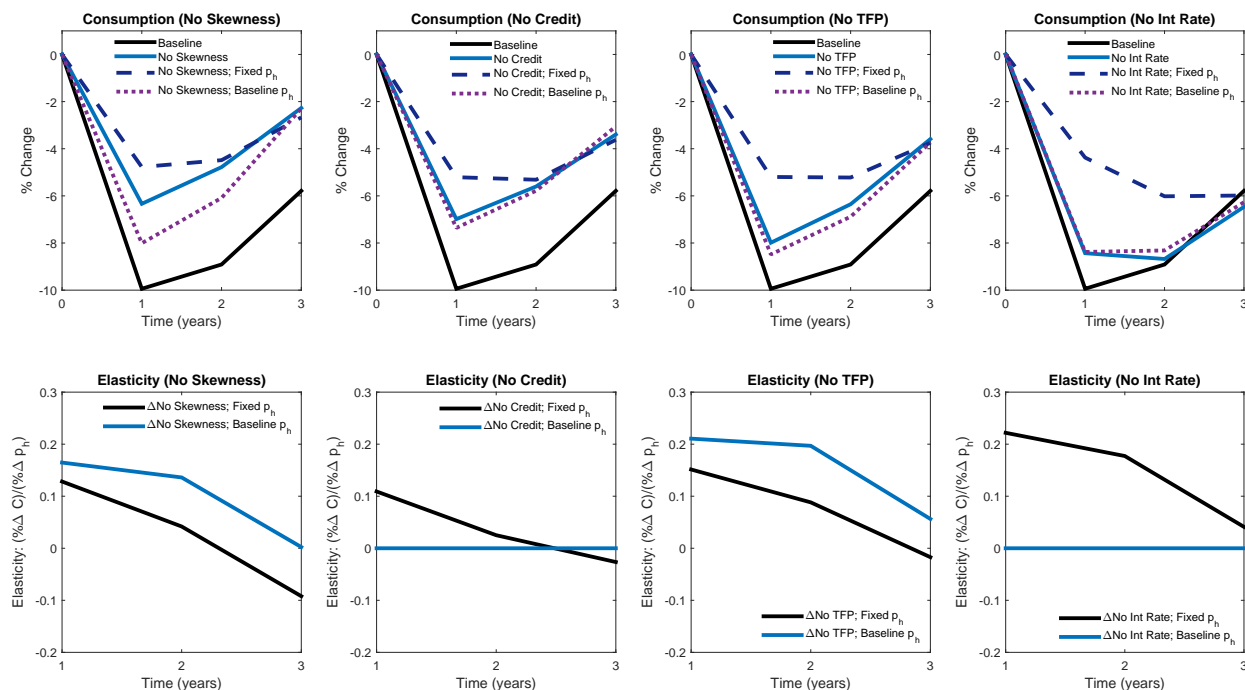


Figure 34: Consumption elasticity to house prices when one shock is removed. The elasticity is calculated by comparing equilibrium consumption to either: (fixed) consumption when house prices are fixed; (baseline) consumption when house prices follow their baseline trajectory.

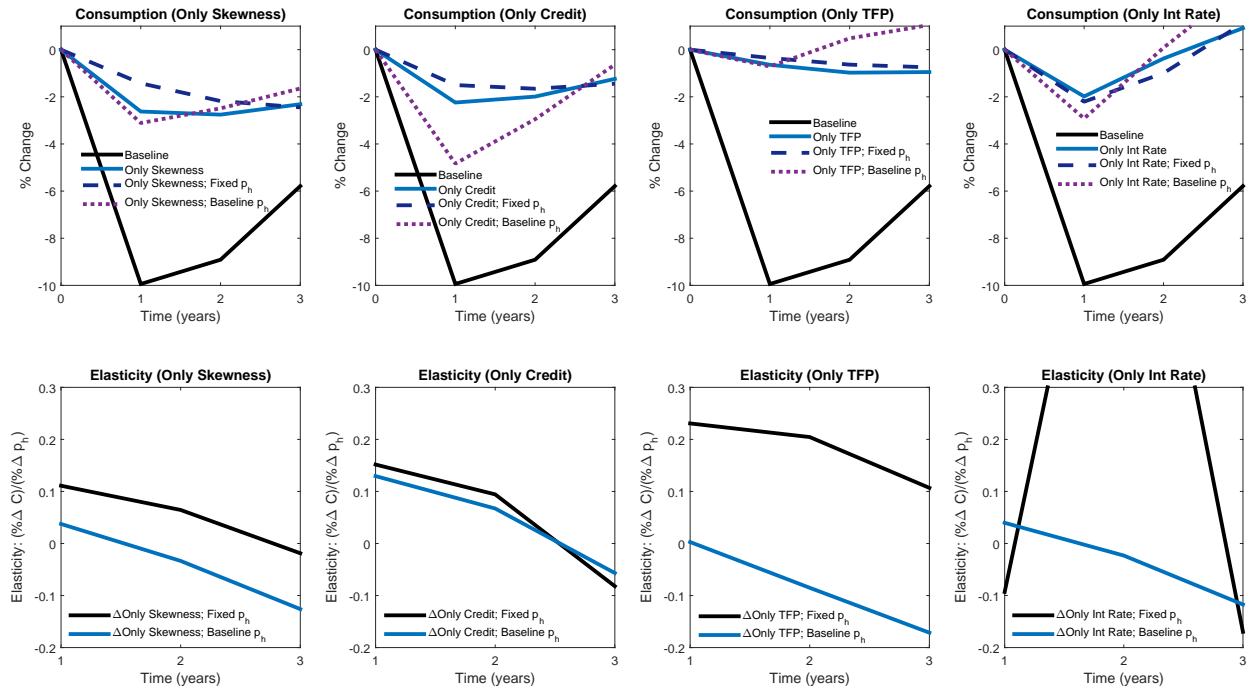


Figure 35: Consumption elasticity to house prices when *the other* shocks are removed. The elasticity is calculated by comparing equilibrium consumption to either: (fixed) consumption when house prices are fixed; (baseline) consumption when house prices follow their baseline trajectory.

B.5.2 Balance Sheet Depth and Consumption in the Cross Section

The main text points out that endogenous housing liquidity amplifies consumption differentially throughout the cross-section. In particular, selling delays increase the mass of the left tail of the consumption decline histogram for highly leveraged and distressed owners, as shown in figure 36. By contrast, renters are sheltered from the debt overhang caused by decreasing liquidity.

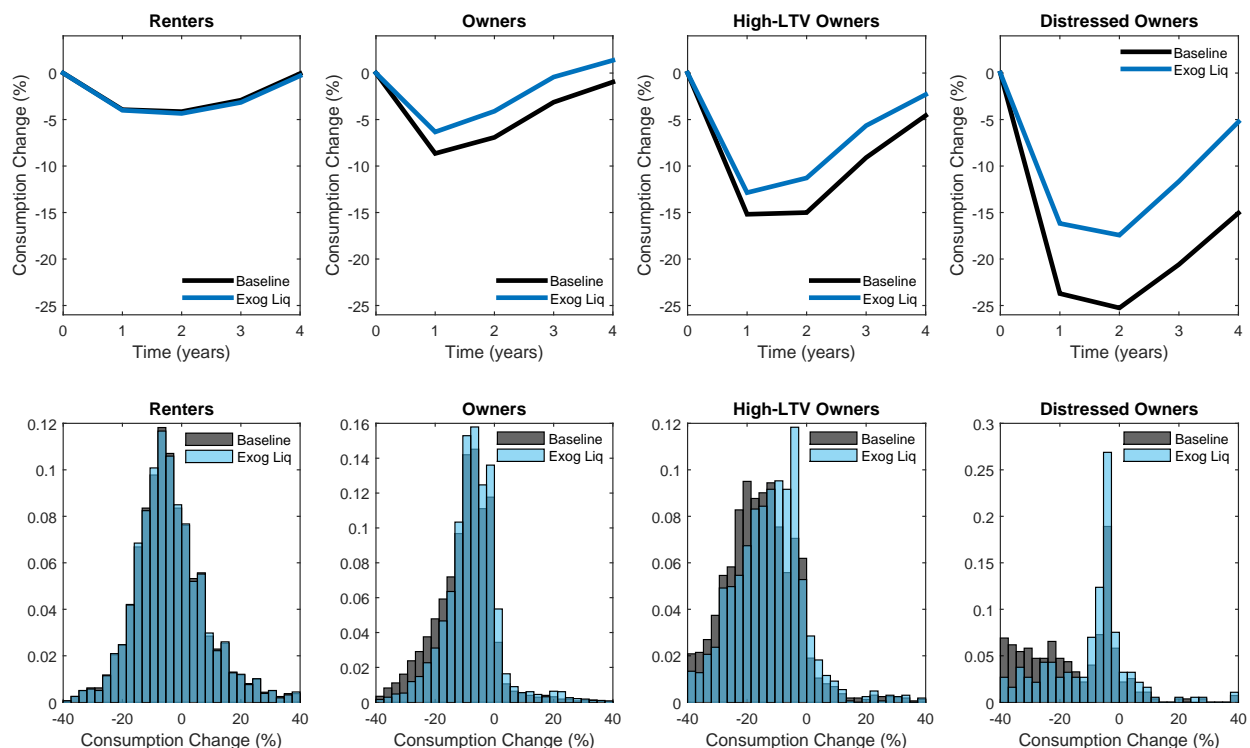


Figure 36: The amplification effects of endogenous liquidity on consumption. High loan-to-value (LTV) is above 0.8. Distressed owners are those who default 1 year *after* the beginning of the Great Recession. The histograms show the distribution of consumption changes during the bust.

Figure 37 corresponds to table 7 in section 5.3.2, which discusses the importance of balance sheet depth for the behavior of consumption during the crisis. The top row plots slices of average consumption over time by net worth bin, and the bottom row shows the entire distribution of the peak-to-trough decline in consumption for each of these groups.

Figure 38 refers to the discussion in section 38 about the higher order consumption implications of balance sheet depth. The bottom left panel shows that homeowners are better able than renters to insure against income shocks during normal times. However, the middle left panel provides a stark depiction of the deterioration in the risk properties of leveraged homeownership, as the left tail of consumption dynamics expands to the left for owners relative to renters. Similar patterns emerge when comparing homeowners with different amounts of leverage to each other, as shown in the middle column. Lastly, the column on the right reveals that distressed owners who are least able to extract equity

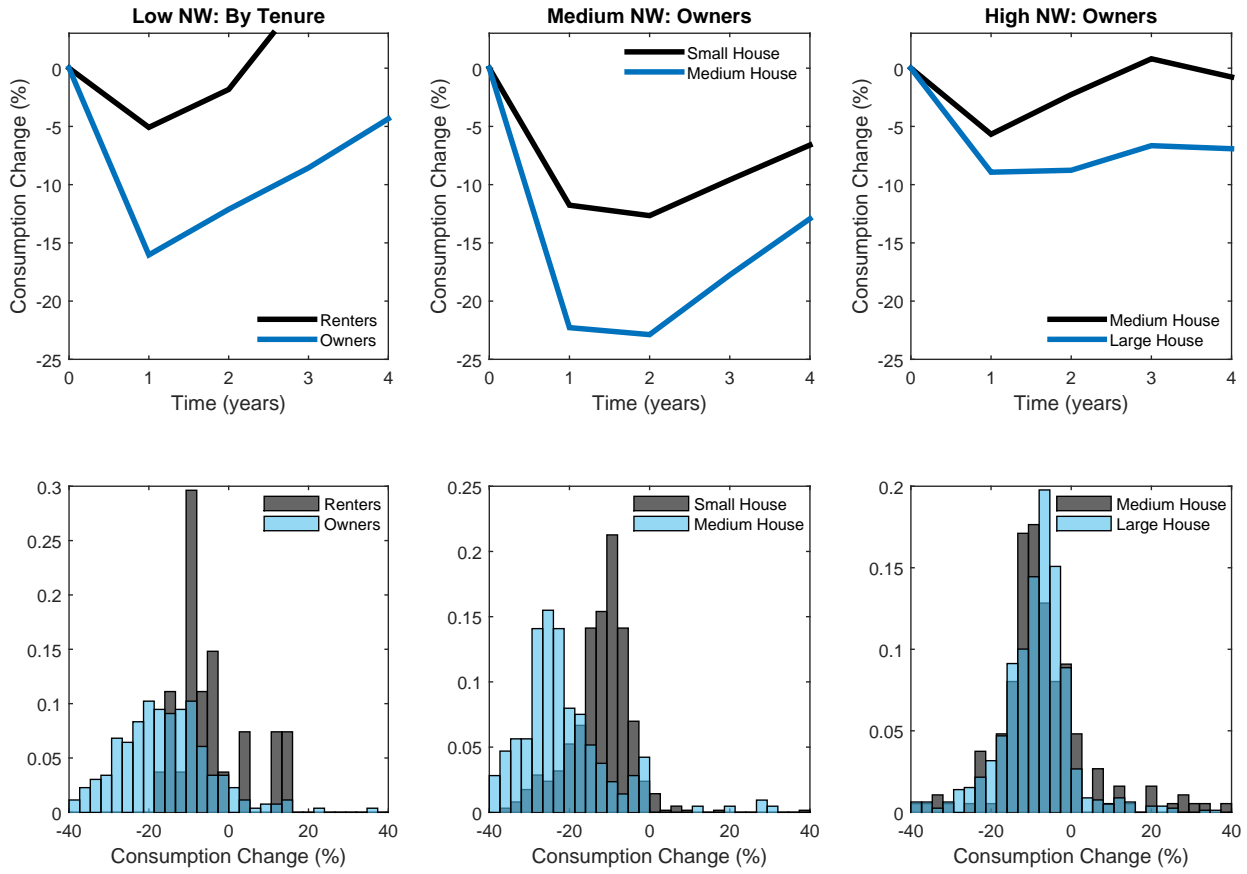


Figure 37: Consumption by net worth (NW) decile and balance sheet depth. Low NW is decile 4; medium NW is decile 6; high NW is decile 9.

either by selling (because of debt overhang) or refinancing (because of their default risk) suffer the largest consumption declines. Triggering the default option provides considerable consumption relief, though at the expense of eviction and several years of exclusion from the mortgage market.

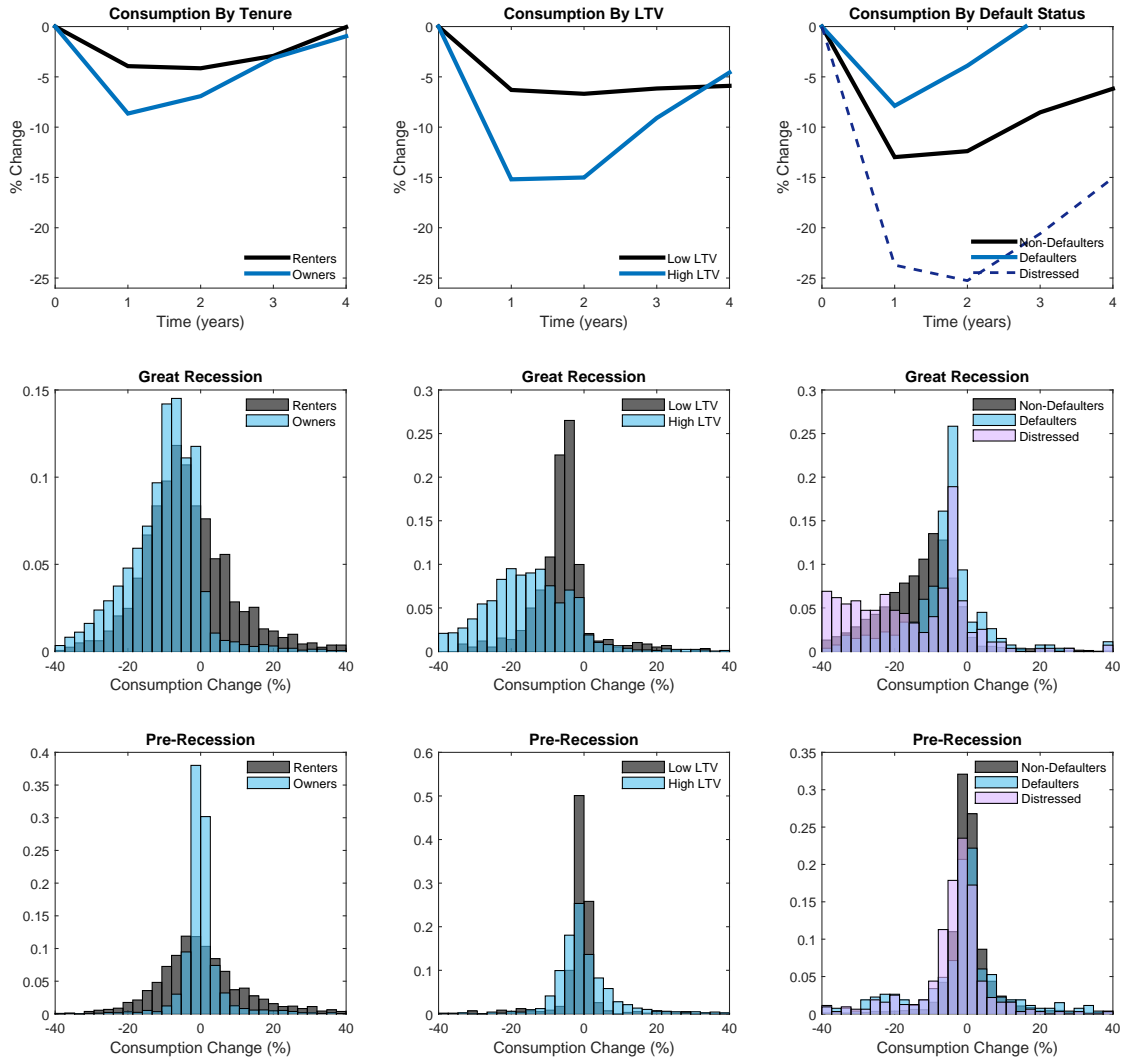


Figure 38: Consumption by tenure status, leverage, and financial distress. Low loan-to-value (LTV) is below 0.3; high LTV is above 0.8. Distressed owners are those who default 1 year *after* the beginning of the Great Recession. The middle row of histograms shows the distribution of consumption changes during the Great Recession. The bottom row displays the dispersion in pre-recession consumption dynamics.

B.6 Mortgage Rate Reductions and Heterogeneity

Section 5.4 refers to figure 39 when it describes the ability of mortgage rate reductions to stimulate house prices during the crisis, which in turn accelerates the recovery of consumption by partially repairing household balance sheets. Figure 40 provides additional cross-sectional support for this mechanism by showing that the potency of the policy increases with leverage. Specifically, highly leveraged owners experience the largest consumption boost.

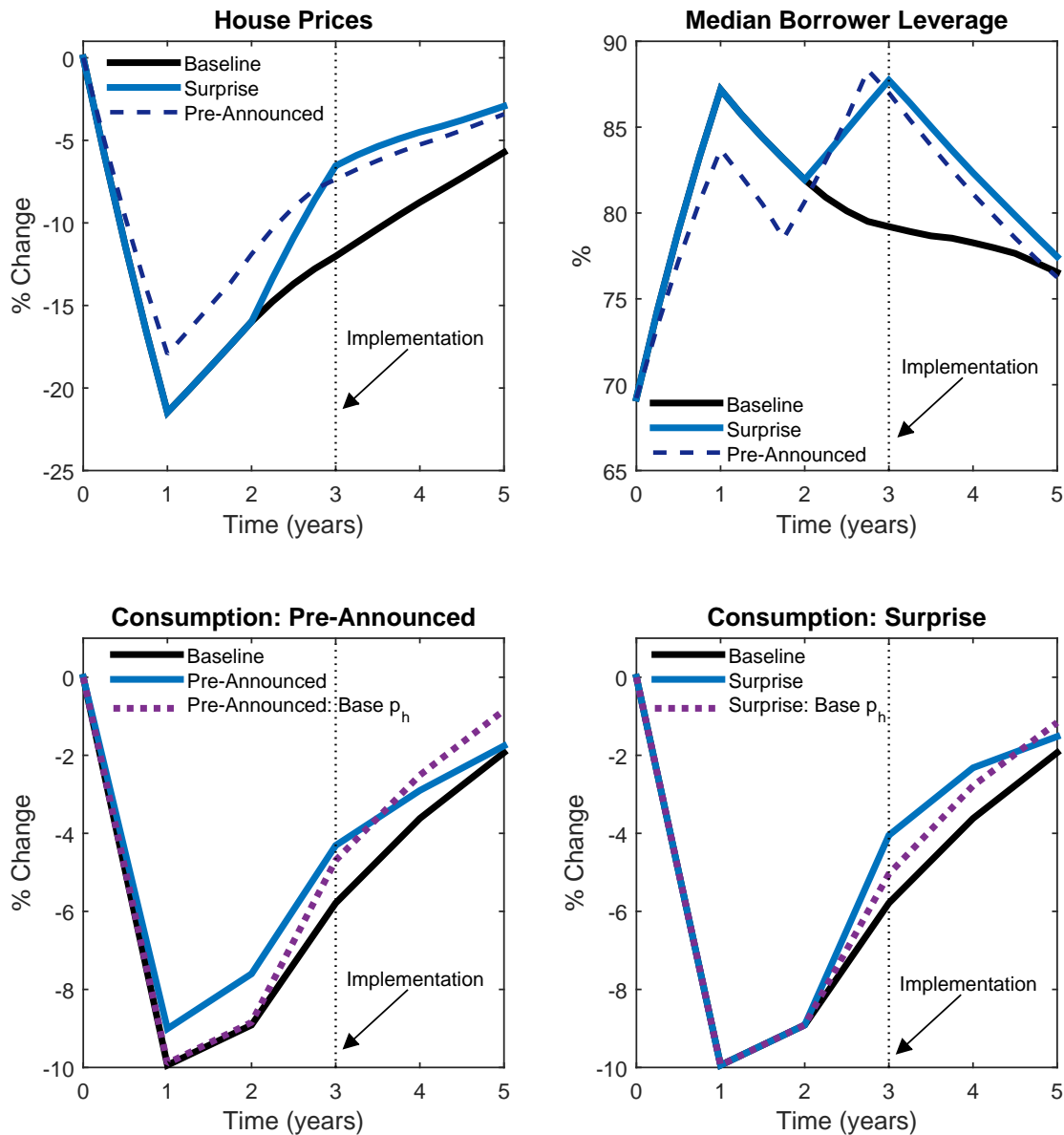


Figure 39: The effects of lowering mortgage rates at $t = 3$ when either pre-announced at the time of the shocks or else implemented by surprise.

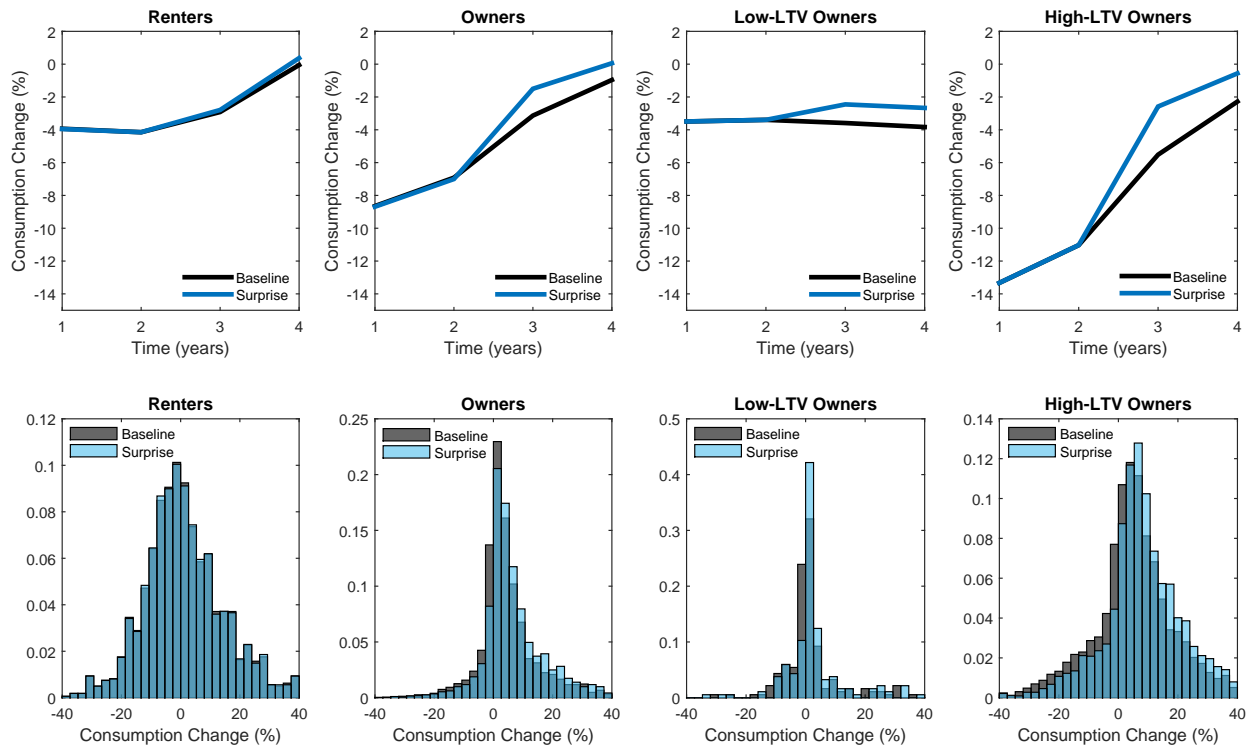


Figure 40: Consumption response to the mortgage rate reduction policy by tenure status and leverage. Low loan-to-value (LTV) is below 0.3; high LTV is above 0.8.

C Model Equations and Equilibrium

This section gives the complete definition of equilibrium from section 3.6.

C.1 Household Value Functions

C.1.1 Consumption and Balance Sheet Decisions

Homeowners who take out a new mortgage:

$$V_t^{own,0}(y_t, h, z_t) = \max_{\substack{m_{t+1} \geq 0, \\ b_{t+1} \geq 0, \\ c_t \geq 0}} u(c_t, h) + \beta \mathbb{E} \left[\begin{array}{l} (1 - \delta_h)[W_{t+1}^{own,0}(y_{t+1}, (r_{t+1}, m_{t+1}), h, z_{t+1}) \\ + R_{t+1}^{sell,0}(y_{t+1}, (r_{t+1}, m_{t+1}), h, z_{t+1})] \\ + \delta_h[V_{t+1}^{rent,0}(y_{t+1}, z_{t+1}) + R_{t+1}^{buy,0}(y_{t+1}, z_{t+1})] \end{array} \right] \quad (15)$$

subject to

$$\begin{aligned} c_t + \gamma p_t h + b_{t+1}/(1 + i_{t+1}) &\leq y_t + q_t((r_{t+1}, m_{t+1}), b_{t+1}, h, z_t)m_{t+1} \\ q_t((r_{t+1}, m_{t+1}), b_{t+1}, h, z_t)m_{t+1} &\leq \vartheta p_t h \\ y_{t+1} &= w_{t+1}e_{t+1}z_{t+1} + b_{t+1} \end{aligned}$$

Homeowners who make a payment on their current mortgage:

$$V_t^{amort}(y_t, (\bar{r}, m_t), h, z_t) = \max_{\substack{b_{t+1} \geq 0, \\ c_t \geq 0, \\ l_t}} u(c_t, h) + \beta \mathbb{E} \left[\begin{array}{l} (1 - \delta_h)[W_{t+1}^{own,0}(y_{t+1}, (\bar{r}, m_{t+1}), h, z_{t+1}) \\ + R_{t+1}^{sell,0}(y_{t+1}, (\bar{r}, m_{t+1}), h, z_{t+1})] \\ + \delta_h[V_{t+1}^{rent,0}(y_{t+1}, z_{t+1}) + R_{t+1}^{buy,0}(y_{t+1}, z_{t+1})] \end{array} \right]$$

subject to

$$\begin{aligned} c_t + \gamma p_t h + b_{t+1}/(1 + i_{t+1}) + l_t &\leq y_t \\ \frac{\bar{r}}{1 + \bar{r}}m_t &\leq l_t \leq m_t \\ m_{t+1} &= (m_t - l_t)(1 + \bar{r}) \\ y_{t+1} &= w_{t+1}e_{t+1}z_{t+1} + b_{t+1} \end{aligned} \quad (16)$$

Homeowners who default but are not foreclosed on:

$$V_t^{delinq}(y_t, (\bar{r}, m_t), h, z_t) = \max_{\substack{b_{t+1} \geq 0, \\ c_t \geq 0}} u(c_t, h) + \beta \mathbb{E} \left[\begin{array}{l} (1 - \delta_h)[W_{t+1}^{own,0}(y_{t+1}, (\bar{r}, m_t), h, z_{t+1}) \\ + R_{t+1}^{sell,0}(y_{t+1}, (\bar{r}, m_t), h, z_{t+1})] \\ + \delta_h[V_{t+1}^{rent,0}(y_{t+1}, z_{t+1}) + R_{t+1}^{buy,0}(y_{t+1}, z_{t+1})] \end{array} \right]$$

subject to

$$\begin{aligned} c_t + \gamma p_t h + b_{t+1}/(1 + i_{t+1}) &\leq y_t \\ y_{t+1} &= w_{t+1}e_{t+1}z_{t+1} + b_{t+1} \end{aligned} \quad (17)$$

Homeowners with a default flag:

$$\begin{aligned}
V_t^{own,1}(y_t, h, z_t) = \max_{b_{t+1}, c_t \geq 0} & u(c_t, h) + \beta \mathbb{E} \left[\begin{aligned} & (1 - \delta_h) \{ (1 - \lambda_f) [W_{t+1}^{own,0}(y_{t+1}, 0, h, z_{t+1}) \\ & + R_{t+1}^{sell,0}(y_{t+1}, 0, h, z_{t+1})] \\ & + \lambda_f [V_{t+1}^{own,1}(y_{t+1}, h, z_{t+1}) + R_{t+1}^{sell,1}(y_{t+1}, h, z_{t+1})] \} \\ & + \delta_h \{ (1 - \lambda_f) [V_{t+1}^{rent,0}(y_{t+1}, z_{t+1}) + R_{t+1}^{buy,0}(y_{t+1}, z_{t+1})] \\ & + \lambda_f [V_{t+1}^{rent,1}(y_{t+1}, z_{t+1}) + R_{t+1}^{buy,0}(y_{t+1}, z_{t+1})] \} \end{aligned} \right] \\
& \text{subject to} \\
& c_t + \gamma p_t h + b_{t+1}/(1 + i_{t+1}) \leq y_t \\
& y_{t+1} = w_{t+1} e_{t+1} z_{t+1} + b_{t+1}
\end{aligned} \tag{18}$$

Renters with good credit:

$$\begin{aligned}
V^{rent,0}(y_t, z_t) = \max_{\substack{b_{t+1}, c_t \geq 0, \\ 0 \leq a_t \leq \bar{a}}} & u(c_t, a_t) + \beta \mathbb{E} \left[V_{t+1}^{rent,0}(y_{t+1}, z_{t+1}) + R_{t+1}^{buy,0}(y_{t+1}, z_{t+1}) \right] \\
& \text{subject to} \\
& c_t + b_{t+1}/(1 + i_{t+1}) + r_a a_t \leq y_t \\
& y_{t+1} = w_{t+1} e_{t+1} z_{t+1} + b_{t+1}
\end{aligned} \tag{19}$$

Renters with a default flag:

$$\begin{aligned}
V^{rent,1}(y_t, z_t) = \max_{\substack{b_{t+1}, c_t \geq 0, \\ 0 \leq a_t \leq \bar{a}}} & u(c_t, a_t) + \beta \mathbb{E} \left[\begin{aligned} & (1 - \lambda_f) [V_t^{rent,0}(y_t, z_t) + R^{buy,0}(y_t, z_t)] \\ & + \lambda_f [V_t^{rent,1}(y_t, z_t) + R^{buy,1}(y_t, z_t)] \end{aligned} \right] \\
& \text{subject to} \\
& c_t + b_{t+1}/(1 + i_{t+1}) + r_a a_t \leq y_t \\
& y_{t+1} = w_{t+1} e_{t+1} z_{t+1} + b_{t+1}
\end{aligned} \tag{20}$$

C.1.2 House Buying Decisions

The value of searching to buy a house:

$$R_t^{buy,0}(y_t, z_t) = \max\{0, \max_{\substack{h_t \in H, \\ p_t^{bid} \leq y_t - \underline{y}}} \eta_t^{buy}(p_t^{bid}, h_t) [V_t^{own,0}(y_t - p_t^{bid}, h_t, z_t) - V_t^{rent,0}(y_t, z_t)]\} \tag{21}$$

$$R_t^{buy,1}(y_t, z_t) = \max\{0, \max_{\substack{h_t \in H, \\ p_t^{bid} \leq y_t}} \eta_t^{buy}(p_t^{bid}, h_t) [V_t^{own,1}(y_t - p_t^{bid}, h_t, z_t) - V_t^{rent,1}(y_t, z_t)]\} \tag{22}$$

C.1.3 Mortgage Default, Amortization, and Refinancing Decisions

The value function for the decision to default, refinance, or make a payment:

$$W_t^{own,0}(y_t, (\bar{r}, m_t), h, z_t) = \max \left\{ \varphi [V_t^{rent,1}(y_t, z_t) + R_t^{buy,1}(y_t, z_t)] \right. \\ \left. + (1 - \varphi) V_t^{delinq}(y_t, (\bar{r}, m_t), h, z_t), V_t^{amort}(y_t, (\bar{r}, m_t), h, z_t), V_t^{own,0}(y_t - m_t, h, z_t) \right\} \quad (23)$$

C.1.4 House Selling Decisions

The option value of selling for an owner with good credit:

$$R_t^{sell,0}(y_t, (\bar{r}, m_t), h, z_t) = \max \{ 0, \max_{p_t^{list} \geq 0} \eta_t^{sell}(p_t^{list}, h) [V_t^{rent,0}(y_t + p_t^{list} - m_t, z_t) \\ + R_t^{buy,0}(y_t + p_t^{list} - m_t, z_t) - W_t^{own,0}(y_t, (\bar{r}, m_t), h, z_t)] + [1 - \eta_t^{sell}(p_t^{list}, h)] (-\xi) \} \quad (24)$$

subject to

$$p_t^{list} \geq m_t - y_t$$

The option value of selling for an owner with a default flag:

$$R_t^{sell,1}(y_t, 0, h, z_t) = \max \{ 0, \max_{p_t^{list} \geq 0} \eta_t^{sell}(p_t^{list}, h) [V_t^{rent,1}(y_t + p_t^{list}, z_t) \\ + R_t^{buy,1}(y_t + p_t^{list}, z_t) - V_t^{own,1}(y_t, h, z_t)] + [1 - \eta_t^{sell}(p_t^{list}, h)] (-\xi) \} \quad (25)$$

C.2 Production

C.2.1 Composite Consumption

The optimality condition for numeraire good production is

$$w_t = Z_t \quad (26)$$

C.2.2 Apartment Space

The optimality condition for apartment space production is

$$r_a = \frac{1}{A} \quad (27)$$

C.2.3 Housing Construction

The optimality conditions for new housing construction are

$$1 = p_t \frac{\partial F_h(\bar{L}, S_{ht}, N_{ht})}{\partial S_{ht}} \quad (28)$$

$$w_t = p_t \frac{\partial F_h(\bar{L}, S_{ht}, N_{ht})}{\partial N_{ht}} \quad (29)$$

C.3 Financial Sector

The interest rate for new mortgages satisfies

$$1 + r_{t+1} = \frac{(1 + \phi)(1 + i_{t+1}^{LR})}{1 - \delta_h} \Rightarrow r_{t+1} \approx i_{t+1}^{LR} + \phi + \delta_h \quad (30)$$

where i_{t+1}^{LR} is the *long-run* cost of external financing (e.g. the 10-year treasury rate) that can deviate from the short-run rate i_{t+1} outside of steady state.

Mortgage prices satisfy the recursive relationship

$$(1 + \zeta)q_t((\bar{r}, m_{t+1}), b_{t+1}, h, z_t) = \frac{1}{1 + r_{t+1}} \mathbb{E} \left\{ \underbrace{\eta_{t+1}^{sell}}_{\text{sell, repay}} + \underbrace{(1 - \eta_{t+1}^{sell})}_{\text{no house sale}} \left[\underbrace{d_{t+1}^*}_{\text{default}} \overbrace{\varphi \min \left\{ 1, \frac{J_{t+1}^{REO}(h)}{m_{t+1}} \right\}}^{\text{foreclosure recovery ratio}} \right. \right. \right. \\ \left. \left. \left. + \underbrace{d_{t+1}^*(1 - \varphi)(1 + \zeta)q_{t+1}^{delinq}}_{\text{delinquency continuation value}} + (1 - d_{t+1}^*) \left\{ \underbrace{\mathbf{1}_{[\text{Refi}, t+1]}}_{\text{repay in full}} + \mathbf{1}_{[\text{No Refi}, t+1]} \underbrace{\left(\frac{l_{t+1}^* + (1 + \zeta)q_{t+1}^{cont} m_{t+2}^*}{m_{t+1}} \right)}_{\text{payment + continuation value}} \right\} \right] \right\} \\ \text{such that} \\ \eta_{t+1}^{sell} \equiv \eta_s(\theta_s(p_{t+1}^{list*}, h; p_{t+1})) \quad (\text{probability of house sale}) \\ q_{t+1}^{delinq} \equiv q_{t+1}((\bar{r}, m_{t+1}), b_{t+2}^{delinq*}, h, z_{t+1}) \quad (\text{mark-to-market price for delinquent } m_{t+1}) \\ q_{t+1}^{cont} \equiv q_{t+1}((\bar{r}, m_{t+2}^*), b_{t+2}^*, h, z_{t+1}) \quad (\text{mark-to-market price for updated } m_{t+2}^*) \\ m_{t+2}^* = (m_{t+1} - l_{t+1}^*)(1 + \bar{r}) \quad (\text{endogenous amortization}) \quad (31)$$

The value of repossessing a house h is

$$J_t^{REO}(h) = R_t^{REO}(h) - \gamma p_t h + \frac{1 - \delta_h}{1 + i_{t+1}} J_{t+1}^{REO}(h) \\ R_t^{REO}(h) = \max \left\{ 0, \max_{p_t^{REO} \geq 0} \eta_t^{sell}(p_t^{REO}, h) \left[(1 - \chi) p_t^{REO} - \left(-\gamma p_t h + \frac{1 - \delta_h}{1 + i_{t+1}} J_{t+1}^{REO}(h) \right) \right] \right\} \quad (32)$$

C.4 Housing Market Equilibrium

C.4.1 Market Tightnesses

Market tightnesses satisfy

$$\kappa_b h_t \geq \overbrace{\alpha_{bt}(\theta_{bt}(p_t^{bid}, h_t))}^{\text{prob of match}} \overbrace{(p_t^{bid} - p_t h_t)}^{\text{broker surplus}} \quad (33)$$

$$\kappa_s h_t \geq \overbrace{\alpha_{st}(\theta_{st}(p_t^{list}, h_t))}^{\text{prob of match}} \overbrace{(p_t h_t - p_t^{list})}^{\text{broker surplus}} \quad (34)$$

with $\theta_{bt}(p_t^{bid}, h_t) \geq 0$, $\theta_{st}(p_t^{list}, h_t) \geq 0$, and complementary slackness. Recall that the index p_t is a sufficient statistic for the dependence of tightnesses on the household distribution Φ_t , i.e. $\theta_{bt}(\cdot) \equiv \theta_b(\cdot; p_t(\Phi_t))$ and $\theta_{st}(\cdot) \equiv \theta_s(\cdot; p_t(\Phi_t))$.

C.4.2 Determining the House Price Index

Housing supply $\mathcal{S}_t(p_t)$ includes sales of new construction, owner-occupied houses, and REO inventories:

$$\mathcal{S}_t(p_t) = \overbrace{Y_{ht}(p_t)}^{\text{new housing}} + \overbrace{S_t^{REO}(p_t)}^{\text{REO housing}} + \overbrace{\int h \eta_s(\theta_s(p_t^{list*}, h; p_t)) d\Phi_t^{own}}^{\text{sold by owner}} \quad (35)$$

The supply of REO housing is given by

$$S_t^{REO}(p_t) = \sum_{h \in H} h \eta_s(\theta_s(p_t^{REO}, h; p_t)) \left[\underbrace{H_t^{REO}(h)}_{\text{existing REOs}} + \underbrace{\int d_t^* [1 - \eta_s(\theta_s(p_t^{list*}, h; p_t))] d\Phi_t^{own}(\cdot; h)}_{\text{new foreclosures after a failed listing}} \right] \quad (36)$$

Housing demand $\mathcal{D}_t(p_t)$ equals housing purchased by matched buyers,

$$\mathcal{D}_t(p_t) = \int h_t^* \eta_b(\theta_b(p_t^{bid*}, h_t^*; p_t)) d\Phi_t^{rent} \quad (37)$$

The house price index p_t sets supply equal to demand,

$$\mathcal{D}_t(p_t) = \mathcal{S}_t(p_t) \quad (38)$$

which is reminiscent of Walrasian market clearing. The key difference is that, in this frictional setting, individual buyers and sellers may fail to transact, in which case they do not immediately appear on either side of equation (38). They may, however, influence future demand and supply if they make another attempt to trade in subsequent periods.

C.5 Equilibrium Definition

In a stationary equilibrium, all prices and quantities are constant, and i and r are exogenous because of the open economy assumption. Also, the supply of new permits \bar{L} is exogenous, which removes the need to solve for their price.

Definition 1 *A stationary recursive equilibrium is*

1. Household value functions $R^{sell,f}$, $W^{own,f}$, $R^{buy,f}$, $V^{rent,f}$, $V^{own,f}$, V^{amort} , and their associated policy functions
2. REO value function J^{REO} and its associated policy function p^{REO}
3. Mortgage pricing function q
4. Market tightness functions θ_b and θ_s
5. Prices w , r_a , and p
6. Quantities S_h , N_c , and N_h
7. Stationary distributions H^{REO} of REO properties and Φ of households

such that

1. **Household Optimality:** The value/policy functions solve (15) – (25).
2. **Production Optimality:** Conditions (26) – (29) are satisfied.
3. **Lender Optimality:** Conditions (30) – (32) are satisfied.
4. **Market Tightnesses:** $\theta_b(\cdot; p)$ and $\theta_s(\cdot; p)$ satisfy (33) – (34).
5. **Labor Market Clearing:** $N_c + N_h = \int \int_E e \cdot z F(de) d\Phi$.
6. **House Price Index:** $\mathcal{D}(p) = \mathcal{S}(p)$.
7. **Stationarity:** H^{REO} and Φ are invariant with respect to the Markov process induced by the exogenous processes and relevant policy functions.

D Calibration and Computation

D.1 Income Dynamics

As explained in section 4, quarterly income processes cannot be estimated directly from the PSID because it is annual data. Instead, a labor process is specified akin to that in Storesletten et al. (2004) except without the life cycle or permanent shock at birth. Their values for the autocorrelation of the persistent shock and the variances of the persistent and transitory shocks are transformed into quarterly values in the manner described below.

D.1.1 Persistent Shocks

It is assumed that in each period households play a lottery in which, with probability 3/4, they receive the same persistent shock as they did in the previous period, and with probability 1/4, they draw a new shock from a transition matrix calibrated to the persistent process in Storesletten et al. (2004) (in which case they still might receive the same persistent labor shock). This is equivalent to choosing transition probabilities that match the expected amount of time that households expect to keep their current shock. Storesletten et al. (2004) report an annual autocorrelation coefficient of 0.952 and a frequency-weighted average standard deviation over expansions and recessions of 0.17. The Rouwenhorst method is used to calibrate this process, which gives the following transition matrix:

$$\tilde{\pi}_z(\cdot, \cdot) = \begin{pmatrix} 0.9526 & 0.0234 & 0.0006 \\ 0.0469 & 0.9532 & 0.0469 \\ 0.0006 & 0.0234 & 0.9526 \end{pmatrix}$$

As a result, the transition matrix *prior to adding the fourth state corresponding to the top 1%* is

$$\pi_z(\cdot, \cdot) = 0.75I_3 + 0.25\tilde{g}_z(\cdot, \cdot) = \begin{pmatrix} 0.9881 & 0.0059 & 0.0001 \\ 0.0171 & 0.9883 & 0.0171 \\ 0.0001 & 0.0059 & 0.9881 \end{pmatrix}$$

D.1.2 Transitory Shocks

Storesletten et al. (2004) report a standard deviation of the transitory shock of 0.255. To replicate this, it is assumed that the annual transitory shock is actually the sum of four, independent quarterly transitory shocks. The same identifying assumption as in Storesletten et al. (2004) is used, namely, that all households receive the same initial persistent shock. Any variance in initial labor income is then due to different draws of the transitory shock. Recall that the labor productivity process is given by

$$\ln(e \cdot z) = \ln(e) + \ln(z)$$

Therefore, total labor productivity (which, when multiplied by the wage w , is total wage income) over a year in which s stays constant is

$$(e \cdot z)_{\text{year 1}} = \exp(z_0)[\exp(e_1) + \exp(e_2) + \exp(e_3) + \exp(e_4)]$$

For different variances of the transitory shock, total annual labor productivity is simulated for many individuals, logs are taken, and the variance of the annual transitory shock is computed. It turns out that quarterly transitory shocks with a standard deviation of 0.49 give the desired standard deviation of annual transitory shocks of 0.255.

D.2 Computation

The household problem is solved using value function iteration. The state space $(y, (\bar{r}, m), h, z)$ for homeowners with good credit is discretized using 275 values for y , 2

values for \bar{r} (the long-run mortgage rate and also its value during quantitative easing), 131 values for m , 3 values for h , and 4 values for z . Homeowners with a default flag, $f = 1$, have state (y, h, z) , and renters have state (y, z, f) . To compute the equilibrium transition path, the algorithm starts with an initial guess for the path of the house price index, $\{p_t\}_{t=1}^T$. The algorithm then does backward induction on the recursive mortgage pricing equation and the household Bellman equations before forward iterating on the distribution of households and REO properties. New equilibrium house prices $\{\hat{p}_t\}_{t=1}^T$ are calculated period-by-period during the forward iteration. If the guessed and solved price paths differ, a convex combination of these two sequences is used for the next guess. This process continues until convergence.