Securitization and House Price Growth

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Abstract

In this paper I expand the set of financial factors that can impact the housing and mortgage credit markets by explicitly modeling the securitization of mortgage credit. In doing so I add a new “innovation in securitization” channel through which credit supply shocks can operate and impact the relationship between the housing and mortgage credit markets. I show that this channel generates a co-movement in US house prices and mortgage credit that matches the 2000-2006 period, and explains about half of the increase in house prices and mortgage credit during this period. Innovation in securitization also drives the mortgage spread down, matching the mortgage spread dynamics during this period. Furthermore I show that an alternative credit supply shock that is unrelated to securitization technology generates a counter-factual implication for mortgage credit dynamics. These results support the credit supply view of the 2000s US housing market experience, and in particular suggest that a significant proportion of the house price boom was driven by securitization activities of non-GSE entities.
1 Introduction

The first half of the 2000s were characterized by a boom in US house prices and mortgage credit extended to American households (Figure 1), as well as a decline in mortgage spreads, suggesting that the dynamics in the US mortgage market were driven by an expansion in credit supply.

A debate in the literature exists as to what drove the US housing boom: The demand for or the supply of credit? The credit demand view (see for example: Mian and Sufi (2011), Shiller (2007), and Kaplan et al. (2017)) purports that non-financial factors drove house prices up and households demanded more mortgage credit to finance the purchase of more expensive homes.

The credit supply view suggests that financial innovation and deregulation drove a positive credit supply shock that made available more and cheaper mortgage credit to American households. Mian and Sufi (2009) emphasize the role of sub-prime lending - that is, the increased supply of mortgage credit went to borrowers with higher credit risk who previously did not have easy access to mortgage lending. In contrast, Adelino et al. (2016) show that prime borrowers had more mortgage dollars in default. Ferreira and Gyourko (2015) clarify the picture by showing that it was borrowers who accumulated negative equity in

Figure 1: US Real House Price Index & US Household Mortgage Debt Divided by GDP, 2000Q1 = 100

their property (across all types) that primarily contributed to mortgage defaults. Favara and Imbs (2015) use US branching deregulation as an instrument to show that an exogenous increase in credit supply has a significant and positive impact on house prices.

The empirical work of Ferreira and Gyourko (2015) and Mian and Sufi (2009) emphasize the particular role of non-conforming mortgages in the boom. A non-conforming mortgage is a mortgage that falls outside of the underwriting standards (indexed for example by borrower FICO score, level of documentation, or total loan size) that would make the mortgage eligible for purchase and securitization by a Government Sponsored Enterprise (GSE). This suggests that innovations in the institutions that securitized non-conforming mortgages were key to the boom-bust. These institutions, the non-Agency securitizers, were special purpose vehicles (SPVs) owned by commercial banks and investment banks. Figure 2 shows that non-Agency MBS issuance and market share exhibits the same boom-bust timing as the boom-bust in house prices and mortgage credit. Justiniano et al. (2017b) identify a decline in the mortgage rate spread over the 10 Year Treasury that was particularly pronounced in the non-conforming class of mortgages and holds when adjusting for changes in borrower quality.

Figure 2: Non-Agency Mortgage Backed Securitization


1 Also known as “Agencies”, e.g. Fannie Mae, Freddie Mac
Over the early 2000s period mortgage originators were increasingly selling more loans off their balance sheets (Figure 3). Brunnermeier (2009) among others have characterized this as a fundamental shift in the business model of US mortgage credit provision: From a predominantly banks-only system where mortgages, once issued, were kept on banks’ balance sheets (“originate & hold”), to an “originate & distribute” model in which mortgages, once issued, were swiftly pooled and sold off banks’ balance sheets. Figure 3 emphasizes that the increase in mortgages distributed was particularly pronounced in the class of non-conforming mortgages (those securitized by non-Agencies).

![Figure 3: Growth In Mortgage Distribution](image)


In much of the macro modeling literature financial liberalization shocks are defined as a liberalizing shock to the standard Kiyotaki and Moore (1997) collateral constraint households face. For example: Favilukis et al. (2017), and Justiniano et al. (2015), among others. Justiniano et al. (2015) progressively relax the loan-to-value (LTV) constraint on household mortgage debt and find a counter-factually low response of house prices. Their model does not speak to spreads as it has direct saver to borrower lending. Favilukis et al. (2017), by capturing changes in the housing risk premium do generate a quantitatively large response of house prices to a loosening of the collateral constraint. However in their model mortgage rate

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2Mortgages distributed is approximated by MBS issuance (flow) as a percentage of mortgage origination.
spreads counter-factually increase in response to this type of financial market liberalization. To match the dynamics of the mortgage rate they rely on a separate influx of foreign credit shock. Justiniano et al. (2017a) emphasize that collateral constraint liberalization acts as a credit demand shock and in contrast an exogenous shock to credit supply can explain the house price boom and increase in household mortgage debt while also matching the falling mortgage rate spread found in their empirical work Justiniano et al. (2017b).

The existing work relating to the role of credit supply shocks during the 2000s starts with Justiniano et al. (2017a) who show the theoretical role of an exogenous increase in the total quantity of credit available without specifying which institutional, technological or behavioral shift drove this change. The 2000s supply shocks could be operating through a number of channels: for example Greenwald (2018) studies the impact of deregulation of mortgage payment to income limits.

In this paper I expand the set of financial factors that can impact the housing and mortgage credit markets by explicitly modeling the securitization of mortgage credit. In doing so I add a new “innovation in securitization” channel through which credit supply shocks can operate and impact the relationship between the housing and mortgage credit markets. I am also able to separate expansions in credit supply from deterioration in borrower quality. I show that this channel generates a co-movement in house prices and mortgage credit that matches the 2000-2006 period. This shock also drives the mortgage spread down, matching the mortgage spread dynamics during this period.

I build a DSGE model with housing, and two types of financial sector institutions. One, mortgage originating commercial banks who face idiosyncratic risk when retaining their own mortgages on their balance sheet. And two, mortgage securitizing shadow banks who provide commercial banks with the ability to remove idiosyncratic risk from their own balance sheets. Commercial banks are restricted to making home loans to borrowers within their own geographic region. Commercial banks face a region-specific default shock (a proportion of borrowers do not pay back their mortgage loan in full). Banks face a solvency constraint: ex-ante their balance sheet must be such that ex-post they are always able to pay off depositors, even when their region is hit by the default shock. Banks are unable to directly trade claims on mortgage lending with other banks in other regions. The only way commercial
banks can insure themselves against their region-specific risk is to hold mortgage backed securities (MBS). Commercial banks sell pooled mortgages to shadow banks, who have the ability to purchase a diversified set of mortgages across all regions. Shadow banks sell MBS to commercial banks. MBS return the aggregate mortgage market return instead of their region-specific return. Shadow banks face an agency problem: each period the shadow bank can run away with a fraction of their assets (pooled mortgages) instead of repaying MBS. I interpret this fraction as indexing the market trust in the shadow banking sector.

2 The Model

2.1 Overview

The model overlays an island structure onto a RBC model. Each island (indexed by \( i \in [0, 1] \)) contains a continuum of borrower & saver households, a commercial banking sector, and a producer who uses on island labor to produce output that is 1-for-1 convertible into the consumption good.

Figure 5 illustrates the island structure of default. The commercial banking sector on each island may only lend to households on their island. Every period a random fraction \( \psi \) of islands are hit by a “default shock”, similar to Gertler and Kiyotaki (2010)’s island-specific
investment opportunity shock. On “defaulter” islands a fraction $\delta$ of the borrower households fail to repay their mortgage debt\textsuperscript{3}. Figure 6 describes the timing of default shocks.

\textsuperscript{3}This paper focuses on idiosyncratic risk, to address aggregate mortgage market uncertainty $\psi$ and $\delta$ should be made time-varying.
Banks can choose to hold the primary claims on mortgage debt, or to sell them to the off-island securitizing shadow bank. The shadow banking sector purchases primary mortgage claims from each island’s banking sector and packages them into “pass-thru” mortgage backed securities (which payoff based on the aggregate mortgage market return, averaged across islands). Shadow banks are able to divert funds, a la Gertler and Kiyotaki (2010) and Meeks et al. (2017), and therefore are subject to an incentive compatibility constraint.

2.2 Households

Both household types have Greenwood, Hercowitz and Huffman (1988) preferences.

Savers in this model are reflective of older, wealthier individuals who have already purchased a house and do not trade or price housing. Savers’ are relatively patient (discount factor $\tilde{\beta}$), they hold deposits, consume, and work.

Savers’ problem:

$$\max_{\{\tilde{c}_t, \tilde{n}_t, d_t\}} \quad E_0 \sum_{t=0}^{\infty} \tilde{\beta}^t \left( \tilde{c}_t - \frac{\tilde{n}_t^{1+\tilde{\omega}}}{1+\tilde{\omega}} \right)^{1-\tilde{\sigma}}$$

(2.1)
Subject to their budget constraint:

\[ \tilde{c}_t + d_t \leq R_{t-1}d_{t-1} + \bar{w}_t \tilde{n}_t + Div_t \]  \hspace{1cm} (2.2)

Saver specific notation: \( \tilde{c}_t \) denotes consumption of non-durable goods, \( \tilde{n}_t \) labor hours, \( \bar{w}_t \) the wage rate, and \( d_t \) deposits (which pay the risk-free rate \( R_t \)). Finally \( Div_t \) denotes dividends received from commercial and shadow banks, as savers are the ultimate owners of financial institutions.

Borrowers are relatively impatient (discount factor: \( \hat{\beta} < \tilde{\beta} \)), they receive loans for banks, consume, work, and purchase housing using a combination of current income and mortgage loans.

**Borrowers’ problem:**

\[
\max_{\{\hat{c}_t, \hat{h}_t, \hat{n}_t, b_t\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \hat{\beta}^t \left[ \left( \frac{\hat{c}_t - \hat{n}_t^{\frac{1+\sigma}{1+\omega}}} {1-\sigma} \right) + \hat{j}_t \ln \hat{h}_t \right] \]  \hspace{1cm} (2.3)

Subject to their budget constraint:

\[ \hat{c}_t + p_{h,t} \hat{h}_t + (1-\psi\delta)R_{M,t-1}b_{t-1} = b_t + (1-\psi\delta)p_{h,t} \hat{h}_{t-1} + \bar{w}_t \tilde{n}_t \]  \hspace{1cm} (2.4)

And a collateral constraint:

\[ R_{Mt} b_t \leq \bar{m}_t E_{t} p_{h,t+1} \hat{h}_t \]  \hspace{1cm} (2.5)

Where \( \bar{m}_t \) is the exogenous collateral value of housing, and \( p_{h,t} \) is the price of housing. Borrower specific notation: \( \hat{c}_t \) denotes consumption of non-durable goods, \( \hat{n}_t \) labor hours, \( \bar{w}_t \) the wage rate, and \( b_t \) mortgage debt (\( R_{M,t} \) is the mortgage rate). \( \hat{j}_t \) is the housing preference shock, which I will interpret as any factor unrelated to financing conditions that moves house prices.
Borrowers in this model risk share: the aggregate (across island) value of non-defaulted housing and non-defaulted debt enters the borrower budget constraint (2.4). This means the model abstracts from potentially interesting heterogeneity between borrowers with different histories of default. This assumption is required for tractability outside of a heterogeneous agent model of borrowers. However, this treatment still allows commercial banks to face idiosyncratic risk from retaining their own lending, the focus of this paper.

2.3 Production

Each island contains a goods producer who chooses $\tilde{n}_t, \hat{n}_t$ to maximize their profit (2.6) subject to their production function (2.7). Household members can travel costlessly across islands to work and consume, so that wages and prices equalize across islands (alternatively this can be considered as one aggregate producer), the producer problem is:

$$\max_{\tilde{n}_t, \hat{n}_t} Y_t - [\tilde{w}_t \tilde{n}_t + \hat{w}_t \hat{n}_t]$$  \hspace{1cm} (2.6)

subject to

$$Y_t = A_t \tilde{n}_t^\alpha \hat{n}_t^{1-\alpha}$$  \hspace{1cm} (2.7)

2.4 Financial Sector

Figure (7) provides an overview of the balance sheets of financial intermediaries. Capital letters indicate aggregate quantities of the following: mortgage lending (B), commercial bank held loans ($B^c$), shadow bank held loans ($B^b$), commercial bank equity ($N^c$), shadow bank equity ($N^b$), deposits (D), and total issuance of MBS (M). Note: MBS issued by shadow banks ($M^b$) is held entirely within the financial sector by commercial banks ($M^c$), so that $M = M^c = M^b$. 
2.4.1 Commercial Banking Sector

There exists a continuum of commercial banks indexed by \( c \in [0, 1] \). Each period commercial banks choose a specific island on which to locate for the purposes of mortgage lending and deposit taking, so that ex-ante islands have identical mortgage credit markets. In the following period the island’s default status is realized. Commercial banks on all islands receive the same rate of return on MBS held, and must pay back deposits. Commercial banks on defaulter islands are not fully repaid what is owed on mortgage debt. After repaying depositors they die. Commercial banks on non-defaulter islands receive the full amount owed on mortgage debt, repay depositors, and then continue with probability \( \sigma_c \) and die with probability \( 1 - \sigma_c \). Upon death their equity goes to saver households (the ultimate owners of all financial institutions).

The commercial bank’s problem is to choose deposit volumes \( (d_t) \), on balance sheet loans \( (b^c_t) \), and MBS holdings \( (m^c_t) \) to maximize their continuation value subject to their balance sheet identity & to the solvency constraint.
\[
\max_{b^c_t, d_t, m^c_t} V^c_t = E_t \tilde{\Lambda}_{t,t+1} \left[ \begin{array}{c}
(1 - \psi) \\
(1 - \sigma_c)n^c_{t+1} + \sigma_c V^c_{t+1}
\end{array} \right] + \psi n^c_{t+1,\text{def}}
\]

subject to:

Their balance sheet identity:
\[b^c_t + m^c_t = n^c_t + d_t\] (2.9)

The Solvency Constraint:
\[(1 - \delta)R_{M,t} b^c_t + \bar{R}_{m,t} m^c_t \geq R_d d_t\] (2.10)

Where \(\tilde{\Lambda}_{t,t+1}\) is the patient households’ stochastic discount factor. Lower case variables are the bank specific values of their uppercase counterparts in figure 7. Net worth on non-defaulter and defaulter islands is as follows:

\[
n^c_{t+1} = \begin{cases} 
R_{M,t} b^c_t + \bar{R}_{m,t} m^c_t - R_d d_t, & \text{if non-defaulter island} \\
(1 - \delta)R_{M,t} b^c_t + \bar{R}_{m,t} m^c_t - R_d d_t, & \text{if defaulter island}
\end{cases}
\] (2.11)

The solvency constraint is the requirement that, when the banks island is hit with the default shock, its revenue on mortgage lending and MBS holdings must exceed or be equal to its obligation to depositors. Essentially the solvency constraint plays the role of a value-at-risk (VaR) constraint\(^4\) where the probability of defaulting on deposits is 0.

\(^4\)Eg that in Adrian and Shin (2014).
2.4.2 Shadow Banking Sector

Shadow Banks exist off-island. Each period they buy a perfectly diversified set of mortgages from every island and issue MBS which pay the average return on mortgage credit across islands. They die with probability \((1 - \sigma_b)\) and survive with probability \(\sigma_b\). They face an agency problem that follows that in Meeks et al. (2017) and Gertler and Kiyotaki (2010).

The shadow bank’s problem is to purchase diversified mortgage debt \(b_t^b\) and issue MBS \(m_t^b\) subject to their balance sheet identity and incentive compatibility constraint:

\[
\max_{\{b_t^b, m_t^b\}} V_t^b = E_t \bar{\Lambda}_{t,t+1} \left[ (1 - \sigma_b)n_{t+1}^b + \sigma_b V_{t+1}^b \right] (2.12)
\]

subject to:

Their balance sheet identity:

\[
b_t^b = m_t^b + n_t^b (2.13)
\]

The incentive compatibility constraint:

\[
V_t^b \geq \theta_{b,t} b_t^b (2.14)
\]

An individual shadow bank’s net worth evolves according to:

\[
n_{t+1}^b = (1 - \psi \delta) R_{M,t} b_t^b - \bar{R}_{m,t} m_t^b \quad \text{return on the diversified mortgage pool} (2.15)
\]

The shadow bank’s incentive compatibility constraint \((2.14)\) captures the agency problem between a shadow bank and the commercial banks that holds the MBS the shadow bank issues. The literal interpretation of \(\theta_{b,t}\) is as follows: each period the shadow bank is able to
choose to close down and take away a fraction $\theta_{b,t}$ of the amount repaid on the mortgage debt the shadow bank owns. If the shadow bank chooses this they will never be trusted again, they close down and forfeit their continuation value $V_{t}^{b}$. This constraint (2.14) introduces a leverage limit on shadow banks, this limits quantity of MBS they can issue. Essentially $\theta_{b,t}$ indexes the trust that MBS holders place in shadow banks. A fall in $\theta_{b,t}$ captures financial innovation of the sort experience prior to the financial crisis. As the sophistication of shadow banks grew, the view that MBS as an asset could be subject to default fell, and this in turn relaxed the leverage constraints placed on shadow banks by holders of MBS.

Dividing the shadow bank’s bellman (2.12) by the shadow bank’s net worth today ($n_{t}^{b}$) and defining: $\omega_{t}^{b} \equiv \frac{V_{t}^{b}}{n_{t}^{b}}$ and shadow bank leverage $\phi_{t}^{b} \equiv \frac{n_{t+1}^{b}}{n_{t}^{b}}$ the bellman and constraints can be rewritten as:

$$\max_{\{\phi_{t}^{b}\}} \omega_{t}^{b} = E_{t}\tilde{\Lambda}_{t,t+1} \left[ (1 - \sigma_{b}) + \sigma_{b}\omega_{t+1}^{b} \right] \frac{n_{t+1}^{b}}{n_{t}^{b}}$$ (2.16)

subject to:

Their balance sheet identity:

$$\frac{m_{t}^{b}}{n_{t}^{b}} = \phi_{t}^{b} - 1$$ (2.17)

The incentive compatibility constraint:

$$\phi_{t}^{b} \leq \frac{\omega_{t}^{b}}{\theta_{b,t}}$$ (2.18)

An individual shadow bank’s net worth evolves according to:

$$\frac{n_{t+1}^{b}}{n_{t}^{b}} = \left[ (1 - \psi\delta)R_{M,t} - \bar{R}_{m,t} \right] \phi_{t}^{b} + \bar{R}_{m,t}$$ (2.19)

Equation (2.18) makes it clear that the incentive compatibility constraint puts a market based leverage constraint on shadow banks. The market based leverage limit is increasing
in the continuation value $\omega_t^b$ (relative to equity) and decreasing in the shadow bank’s ability to divert ($\theta_{b,t}$).

### 2.5 Aggregates

Evolution of aggregate Bank net worth:

$$N_t^c = (1 - \psi)\left[(\sigma_c + \xi_c)\left(R_{M,t-1}B_{t-1}^c + \bar{R}_{m,t-1}M_{t-1}\right) - \sigma_c R_{t-1}D_{t-1}\right] + \psi\left[(1 - \delta)R_{M,t-1}B_{t-1}^c + \bar{R}_{m,t-1}M_{t-1}^c - R_{t-1}D_{t-1}\right] \tag{2.20}$$

Evolution of aggregate Broker net worth:

$$N_t^b = (\sigma_b + \xi_b)(1 - \psi\delta)R_{M,t-1}B_{t-1}^b - \sigma_b \bar{R}_{m,t-1}M_{t-1} \tag{2.21}$$

### 2.6 Market Clearing

Goods Market equilibrium

$$Y_t - \psi\delta h_t^c + \dot{h}_t = \ddot{c}_t + \dot{c}_t \tag{2.22}$$

Total Housing:

$$\bar{H} = \dot{h}_t \tag{2.23}$$

Total lending:

$$B_t = B_t^c + B_t^b \tag{2.24}$$

MBS market:

$$M_t^c = M_t^b \tag{2.25}$$
3 Calibration

The calibration period is 1990 - 1999, with some exceptions due to data access limitations (indicated below).

Table 1: Standard Calibrations

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Calibration</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>Saver Labor Share</td>
<td>0.79</td>
</tr>
<tr>
<td>$H$</td>
<td>Total Housing Stock</td>
<td>1</td>
</tr>
<tr>
<td>$\hat{\sigma}$</td>
<td>Borrower Risk Aversion</td>
<td>1</td>
</tr>
<tr>
<td>$\tilde{\sigma}$</td>
<td>Saver Risk Aversion</td>
<td>1</td>
</tr>
<tr>
<td>$\hat{\omega}$</td>
<td>Borrower Inverse Frisch Elasticity of Labor Supply</td>
<td>0.5</td>
</tr>
<tr>
<td>$\tilde{\omega}$</td>
<td>Saver Inverse Frisch Elasticity of Labor Supply</td>
<td>0.5</td>
</tr>
</tbody>
</table>

3.1 Calibration of the Financial Parameters

Table 2: Financial Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Calibration</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\beta}$</td>
<td>Saver Discount Rate</td>
<td>0.993</td>
</tr>
<tr>
<td>$\hat{\beta}$</td>
<td>Borrower Discount Rate</td>
<td>0.97</td>
</tr>
<tr>
<td>$\psi$</td>
<td>Probability of Default</td>
<td>0.02</td>
</tr>
<tr>
<td>$\delta$</td>
<td>Foreclosure Cost</td>
<td>0.3</td>
</tr>
<tr>
<td>$\sigma_b$</td>
<td>SBank - Quarterly Survival Probability</td>
<td>0.90</td>
</tr>
<tr>
<td>$\sigma_c$</td>
<td>(not defaulted on) CBanks - Quarterly Survival Probability</td>
<td>$\frac{\sigma_b}{1-\psi}$</td>
</tr>
</tbody>
</table>

I set the saver’s discount rate $\tilde{\beta} = 0.99$ to target an annualized real interest rate of 4.1% and the borrower’s discount rate to $\hat{\beta} = 0.97$ to ensure that borrowers are constrained by their borrowing constraint in steady state.

$\psi$ is the fraction of households defaulting each period. In the literature a mortgage is considered to be in default if the mortgage payments are unpaid (delinquent) for 60 days or
more. Li et al. (2011) find that monthly default rates for mortgages issued in 2004-05 are between 0.16% (prime mortgages) and 1% (subprime), 0.48% and 3% quarterly. Based on these data, and the data in Justiniano et al. (2017b) which suggests that subprime mortgages are 2/3rds of the total mortgage pool, I calibrate \( \psi \) to be a 2% quarterly default rate.

I calibrate \( \sigma_b = 0.90 \) so that the mean survival time of shadow banks is 10 quarters. This matches Meeks et al. (2017). I calibrate \( \sigma_c \) so that the mass of surviving commercial banks, \((1 - \psi)\sigma_c\), is equal to the mass of surviving shadow banks (\(\sigma_b\)). I calibrate \( \bar{m}, j, \theta_b, \xi_b, \) and \( \xi_c \) to jointly hit the steady state targets in Table 3 below.

Table 3: Steady State Targets

<table>
<thead>
<tr>
<th>Variable</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mortgages Distributed (1 - ( \frac{B_c}{B} ))</td>
<td>35%</td>
</tr>
<tr>
<td>Broker Leverage (( \frac{B^b}{N^b} ))</td>
<td>10</td>
</tr>
<tr>
<td>Mortgage Rate (( R_M ))</td>
<td>7.8%</td>
</tr>
<tr>
<td>Loan-to-Value (( \frac{B}{p_h h} ))</td>
<td>85%</td>
</tr>
<tr>
<td>Borrower Debt to (annual) Income</td>
<td>80%</td>
</tr>
</tbody>
</table>

The steady state target for percentage of mortgages distributed (in the non-Agency mortgage pool) comes directly from the data in Ashcraft and Schuermann (2008). I set leverage to 10, this is an educated guess (within the range suggested by Meeks et al. (2017)). I set the real mortgage rate target to match the data in Justiniano et al. (2017b). The steady state LTV target is straightforward and the last target comes from Iacoviello and Neri (2010).

4 Simulation Method

The following simulations involve large shocks (moving the model far away from steady state) and multiple occasionally binding constraints. Therefore, I use a deterministic simulation method with the fully non-linear model. This preserves the integrity of the simulation even as it moves far away from the initial steady state. The non-linearity also allows for all relevant constraints to be occasionally binding. The approach to the deterministic simulation is the extended path approach of Fair and Taylor (1983), which is applied (and explained in more
detail) in Christiano et al. (2015). Let $z_t$ denote the $N \times 1$ vector of endogenous variables determined at time $t$, and $\epsilon_t = \{\theta_{b,t}, \bar{m}_t, \bar{j}_t\}$ the vector of exogenous deterministic variables realized at time $t$. Each period the agents realize an unexpected shock (to either $\theta_{b,t}$, $\bar{j}_t$, or $\bar{m}_t$) and expect the economy to move to a new steady state consistent with the realization of that shock. In $t=1$ the starting point of the deterministic simulation is the initial steady state, in $t \geq 2$ the starting point is the vector of endogenous variables in $t - 1$.

5 The Innovation in Securitization Channel

This section illustrates the effect of a transition to a steady state where the level of mortgage debt is 10% higher. This transition is either driven by 1) a permanent increase in the preference for housing ($j_t$), 2) a permanent increase in the exogenous collateral value of housing ($\bar{m}_t$), or 3) a permanent decrease in the shadow bank’s ability to divert pooled loans $\theta_{b,t}$ (“innovation in securitization”). The transition of the relevant deterministic variable takes place over the first 8 periods, and is a surprise shock each period.

Common to all three experiments is that the collateral constraint (2.5) faced by borrowers does not bind in periods when the shock hits as well as for a number of periods after (see bottom right subplot of figure 8). This result, that shocks that put positive pressure on house prices cause the collateral constraint to become slack, is a general one in models with housing and occasionally binding collateral constraints - for example Guerrieri and Iacoviello (2017).

Because these simulations are deterministic perfect foresight there is no precautionary motive. However, there is an expectations channel - the borrower household anticipates the collateral constraint will bind at some point in the future and this expectation impacts the borrower’s accumulation of mortgage credit.
The higher level of mortgage credit in the new steady state is driven by the following distinct channels in the three experiments. In the “preference” experiment the increased preference for housing ($j_t$) drives upward pressure on house prices because it increases demand for housing (see the pricing equation for housing from the borrower’s housing Euler, 5.1):

$$p_{h,t} = \frac{1}{\lambda_t} \left\{ \frac{j_t}{h_t} + \hat{\beta} E_t\left[ \lambda_{t+1}(1 - \delta \psi)p_{h,t+1} \right] + \hat{\mu}_t \frac{\hat{m}_t E_t p_{h,t+1}}{R_{M,t}} \right\} \quad (5.1)$$

This in turn endogenously relaxes the collateral constraint, driving up borrower demand for mortgage credit. The second experiment, LTV liberalization, exogenously relaxes the collateral constraint - also driving up borrower demand for credit. Because this constraint is binding in equilibrium it enters the borrower’s pricing equation for housing (5.1) and thus LTV liberalization also drives the equilibrium house price up (though this effect is quantitatively limited).

On the credit supply side the innovation in securitization experiment has two effects.
First, the innovation is a reduction in the agency problem faced by shadow banks which means that the spread set by shadow banks falls. Therefore, the equilibrium level of the mortgage rate is lower. The reduced cost of credit relaxes the collateral constraint endogenously and thus raises house prices (see [5.1]) - through a similar channel to LTV liberalization. The second effect operates through the borrower’s inter-temporal consumption decision. The lower equilibrium level of the mortgage rate drives borrowers to bring forward durable & non-durable consumption, simultaneously driving up the demand for housing and credit. The fact that securitization also operates on borrower inter-temporal substitution seems key in matching the quantitative relationship between house prices and mortgage credit.

In terms of the dynamics all three experiments also have two secondary effect - the shock raises future prices with pushes up prices today ([5.1]), and higher house prices endogenously relax the collateral constraint.

The transition dynamics have 3 distinct phases. First, from periods 1-8, the surprise permanent shocks are realized (and the borrower’s collateral constraint is slack each period). Second, from periods 9 - 12, no new shocks are realized but the borrower’s collateral constraint continues to be slack. Third, from period 13 onwards the borrower’s collateral constraint binds. The fact that the periods during which the collateral constraint does and doesn’t bind are the same across all three experiments is not a target of the experiments.

In the first phase (periods 1-8) the borrowers operate on a downward sloping demand curve, because the collateral constraint is slack. The first two experiments (preference and LTV liberalization) are demand for credit shocks. Under these experiments each period the borrower’s demand for credit curve is being shifted rightward, which increases the equilibrium cost of credit. This explains the moderately increasing mortgage rate during this phase (see figure [9]). In contrast the innovation in securitization shock constitutes a supply of credit shock. The shadow bank’s equity (a state variable, $N_b^t$) is the same upon realization of the surprise permanent shock, but given a drop in $\theta_{b,t}$ the shadow bank is able to take more pooled loans onto their balance sheet. This expands the available quantity of mortgage

\footnote{Both the shadow bank’s incentive compatibility constraint and the commercial bank’s solvency constraint never become slack during these experiments.}

\footnote{The drop in $\theta_{b,t}$ outweighs effect of the lower continuation value of the shadow bank ($V_b^t$).}
credit (a rightward shift in credit supply) so the mortgage rate must fall on impact.\footnote{Note: because of the expectations channel - borrower’s expect a new equilibrium where even once the collateral constraint binds again they are able to take on more credit - the mortgage rate is elevated in transition under all 3 experiments because of the increased demand for credit}

The dynamics of the MBS rate in the first phase are subtly different across the experiments. In all three experiments the total quantity of equilibrium credit has increased, which requires that the deposit rate must rise to induce savers to supply more funds for intermediation (and the MBS rate is at a zero spread over the deposit rate). Note the MBS rate in the innovation in securitization experiment is slightly elevated. The path of mortgage credit (see figure 8) is not appreciably different in this experiment. However, the path of shadow bank and commercial bank equity is lower (see figure 10). Therefore, savers must be induced to save even more to compensate for the fall in financial sector equity. This elevates the deposit rate and consequently the rate on MBS.
In the second phase (periods 9 - 12) no additional shocks are realized but the collateral constraint continues to be slack for all three experiments. In all three experiments the mortgage rate rises in period 9, and remains well above its new steady state level in periods 10-12. These dynamics are driven by the borrowers’ expectations channel: The borrowers anticipate the new higher level of equilibrium mortgage credit they are able to accumulate and continue to demand more credit. Lastly the jump in the risk adjusted mortgage spread in period 9 (see figure 8) is driven by the shadow bank’s agency problem. In the securitization experiment shadow bank equity is below its level in the other two experiments (see figure 10). In the previous 8 periods continued realizations of innovation in securitization shocks kept the mortgage spread depressed on impact. However, because no further shocks are realized in period 9 the shadow bank’s lower level of equity combine with incentive compatibility constraint requires it to raise the spread it charges. After period 9 shadow bank equity is growing in all three experiments so the dynamics of the spread are the same (however the level is not).

Finally in period 13 the collateral constraint starts to bind again. Mortgage rates fall because the binding collateral constraint moderates borrower demand for credit. The newly binding collateral constraint combine with the expectations channel and evolution of financial institution net worth mean that variables transition smoothly to their new steady state values.
6 Boom-Bust Simulation Results & Discussion

6.1 Full Boom-Bust Simulation

In this simulation all three shocks \( \{j_t, \bar{m}_t, \theta_{b,t}\} \)8 are used to target the following. First, growth in house prices of 54% to match the Shiller house price index data. Second, growth in mortgage credit of 64% (also to match the data in figure 1). Loan-to-value increase of 10% points (85% to 95%). The latter two targets are matched subject to not exceeding the house price growth target.

Table 4: Full Boom-Bust Simulations - Shock Decomposition

<table>
<thead>
<tr>
<th>Variable (% of Data Explained)</th>
<th>Preference Shocks</th>
<th>LTV Liberalization</th>
<th>Securitization Boom</th>
</tr>
</thead>
<tbody>
<tr>
<td>House Prices (100%)</td>
<td>27%</td>
<td>17%</td>
<td>56%</td>
</tr>
<tr>
<td>Mortgages Credit (90%)</td>
<td>16%</td>
<td>31%</td>
<td>53%</td>
</tr>
<tr>
<td>Mortgages Distributed (57%)</td>
<td>7%</td>
<td>12%</td>
<td>81%</td>
</tr>
<tr>
<td>Spread (Fall) (78%)</td>
<td>0%</td>
<td>0%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 4 summarizes the simulation results. The values in the last three columns are the percentage of the full boom-bust simulation explained by the specified shock. Innovation in securitization explains about half of the growth in house prices and mortgage debt seen in the data (see figure 11), and is the only driver of a fall in the cost of mortgage credit (this last result is not a target of the simulation). While the innovation in securitization channel is not the only driver of mortgage distribution (that is mortgages being increasingly sold off commercial bank balance sheets) it is the primary driver. The other two channels (preference shock and LTV liberalization) do endogenously relax the shadow bank’s leverage.

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8Housing preference \( (j_t) \), LTV liberalization \( (\bar{m}_t) \), and innovation in securitization \( (\theta_{b,t}) \).
9In figure 11, the shocks are removed 1 by 1. “All” is the fully simulation, “SBank + LTV” is the innovation in securitization and LTV liberalization shocks only, and “SBank only” is the innovation in securitization shocks only.
constraint but only the innovation in securitization shocks fundamentally change the shadow banks’ ability to securitize as outlined in the proceeding section.

As is consistent with the results of the proceeding section LTV liberalization has a larger impact on mortgage credit growth (about double) relative to its impact on house price growth. LTV liberalization shocks here primarily exist to help the simulation match the increasing borrower leverage found in the data, though figure 12 shows that the simulation fails to match the gradually increasing household leverage found in the data. This is because the collateral constraint is slack in the boom period making this data dynamic difficult to match.
Figure 12: Loan-to-Value Dynamics

Figure 13 show that mortgage spread falls during the boom period, which is consistent with the innovation in securitization channel driving most of the dynamics of the mortgage spread. Interestingly shadow banking leverage is far more volatile than commercial banking leverage. This suggests that regulatory intervention that simply targets the commercial bank’s equity requirement level will not be effective (as it may very well be slack or only affect a level shift).

Figure 13: Boom-Bust Simulation
Finally figure 14 shows that the opposite dynamics of borrower and saver consumption push moderate the overall macroeconomic effect of financial and housing market shocks in this model.

![Figure 14: Boom-Bust Simulation](image)

6.2 Alternative Credit Supply Shock

![Figure 15: Boom-Bust Simulation](image)

Figure 15 plots the Shadow Bank only shocks from the previous simulations, against a decline (and then recovery) in the savers’ discount factor ($\tilde{\beta}$) calibrated to generate the same expansion of mortgage credit. In this closed economy model this shock is a stand in for an influx of foreign credit. This shock drives the deposit rate down as well as the mortgage rate.
Therefore, through the depression in the equilibrium cost of credit it drives mortgage lending and house prices up through a similar channel to innovation in securitization. However, it has a counter-factual implication for the mortgage spread. Suggesting that though an influx of foreign credit is certainly a credit shock it is likely not the credit shock that drove the US housing and mortgage market during the 2000s.

7 Conclusion

This paper shows that innovations in the mortgage backed securities market can quantitatively match the co-movement of mortgage debt and house prices seen in the 2000-2006 US data. This adds to the debate between credit supply and demand factors as a driver of the 2000s boom bust and shows that innovations in the MBS market act as a credit supply shock discussed by Justiniano et al. (2017a). Furthermore it shows that alternative credit supply shocks that do not impact securitization technology generate counter-factual implications for mortgage spread dynamics during the 2000s.
References


Shiller, Robert J., “Understanding recent trends in house prices and homeownership,”
Model Equations

Auxiliary Expressions:

Aux 1:
\[ \tilde{\Lambda}_{t,t+1} = \beta \frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t} \]

Aux 2:
\[ \Omega^c_{t+1} := (1 - \sigma_c) + \sigma_c \left( \gamma^c_{t+1} R_{t+1} + v^c_{t+1} \right) \]

Aux 3:
\[ \Omega^b_{t+1} := (1 - \sigma_b) + \sigma_b \left( \mu^b_{M,t+1} \phi^b_{t+1} + v^b_{mt} \right) \]

Saver FOCs

\[ \tilde{\lambda}_t = \left[ \tilde{c}_t - \frac{\tilde{n}_t^{1+\tilde{\omega}}}{1 + \tilde{\omega}} \right]^{-\tilde{\sigma}} \]
\[ \check{\lambda}_t = \tilde{\beta} E_t \tilde{\lambda}_{t+1} R_t \]
\[ \hat{n}_t^\theta = \tilde{\omega}_t \]

Borrower FOCs

\[ \hat{\lambda}_t = \left[ \hat{c}_t - \hat{n}_t^{1+\hat{\omega}} \right]^{-\hat{\sigma}} \]
\[ \frac{j_t}{\hat{h}_t} - \hat{\lambda}_t \hat{p}_{h,t} + \hat{\beta} E_t \left[ \hat{\lambda}_{t+1}(1 - \psi \delta) \hat{p}_{h,t+1} \right] + \hat{\mu}_t \frac{\hat{m}_t E_t \hat{p}_{h,t+1}}{R_{M,t}} = 0 \]
\[ \hat{\lambda}_t - \hat{\beta} E_t \left[ \hat{\lambda}_{t+1}(1 - \psi \delta) R_{M,t} \right] - \hat{\mu}_t = 0 \]
\[ \hat{n}_t^\theta = \hat{\omega}_t \]
\[ \hat{c}_t + \hat{p}_{h,t} \hat{h}_t + (1 - \psi \delta) R_{M,t-1} B_{t-1} = B_t + (1 - \psi \delta) \hat{p}_{h,t} \hat{h}_{t-1} + \hat{\omega}_t \hat{n}_t \]
\[ R_{M,t} B_t \leq m_t E_t \hat{p}_{h,t+1} \hat{h}_t \]

Production

\[ Y_t = A_t \tilde{n}_t^\alpha (\tilde{n}_t)^{1-\alpha} \]
\[
\bar{w}_t = \frac{\alpha Y_t}{n_t} 
\]  
(A.11)

\[
\hat{w}_t = \frac{(1 - \alpha)Y_t}{n_t} 
\]  
(A.12)

**Commercial Bank**

Solvency Constraint (binding if \( \gamma^c_t \geq 0 \)):

\[
(1 - \delta)R_{Mt,B_t^c} + \bar{R}_{m,t}M_t^c - R_tD_t \geq 0 
\]  
(A.13)

FOC wrt on balance sheet loans

\[
(v_{Mt}^t - v_t^c) + \gamma_t^c \left( (1 - \delta)R_{Mt} - R_t \right) = 0 
\]  
(A.14)

FOC wrt MBS

\[
(\bar{v}_{mt}^c - v_t^c) + \gamma_t^c \left( \bar{R}_{m,t} - R_t \right) = 0 
\]  
(A.15)

Marginal Value on on-balance sheet loans:

\[
v_{Mt}^c = \mathbb{E}_{t} \tilde{A}_{t,t+1} \left\{ [(1 - \psi)\Omega_{t+1}^c + \psi] R_{Mt} - \psi\delta R_{Mt} \right\} 
\]  
(A.16)

Marginal value on MBS:

\[
\bar{v}_{mt}^c = \mathbb{E}_{t} \tilde{A}_{t,t+1} [(1 - \psi)\Omega_{t+1}^c + \psi] \bar{R}_{m,t} 
\]  
(A.17)

Marginal Value of Deposits:

\[
v_t^c = \mathbb{E}_{t} \tilde{A}_{t,t+1} [(1 - \psi)\Omega_{t+1}^c + \psi] R_t 
\]  
(A.18)

Aggregate net worth:

\[
N_t^c = (1 - \psi) \left[ (\sigma_c + \xi_c) \left( R_{Mt-1}B_{t-1}^c + \bar{R}_{m,t-1}M_{t-1}^c \right) - \sigma_c R_{t-1}D_{t-1} \right] + \psi \left[ (1 - \delta)R_{Mt-1}B_{t-1}^c + \bar{R}_{m,t-1}M_{t-1}^c - R_{t-1}D_{t-1} \right] \]  
(A.19)

Balance sheet:

\[
D_t + N_t^c = B_t^c + M_t^c 
\]  
(A.20)
Shadow Bank:

FOC wrt loans:

\[
\mu_{M,t}^b = \frac{\lambda^b \theta_{b,t}}{1 + \lambda^b_t} \tag{A.21}
\]

Incentive compatibility constraint (binding if \(\lambda^b_t \geq 0\)):

\[
\phi^b_t \leq \frac{\bar{v}_{mt}^b}{\theta_{b,t} - \mu_{M,t}^b} \tag{A.22}
\]

Marginal Value of Loans (Note: \(\mu_{M,t}^b := v_{Mt}^b - \bar{v}_{mt}^b\)):

\[
\mu_{M,t}^b = E_t \tilde{\Lambda}_{t,t+1} \Omega_{t,t+1}^b \left[ (1 - \psi \delta) R_{Mt} - \bar{R}_{mt} \right] \tag{A.23}
\]

Marginal Value of MBS:

\[
\bar{v}_{mt}^b = E_t \tilde{\Lambda}_{t,t+1} \Omega_{t,t+1}^b \bar{R}_{mt} \tag{A.24}
\]

Balance Sheet Identity:

\[
B_t^b = N_t^b + M_t^b \tag{A.25}
\]

Aggregate Shadow Bank Net Worth:

\[
N_t^b = (\sigma_b + \xi_b)(1 - \psi \delta) R_{M,t-1} B_{t-1}^b - \sigma_b \bar{R}_{m,t-1} M_{t-1}^b \tag{A.26}
\]

Shadow Bank leverage:

\[
\phi^b_t = \frac{B_t^b}{N_t^b} \tag{A.27}
\]

Market Clearing:

\[
\bar{H} = \hat{h}_t \tag{A.28}
\]

\[
Y_t = \tilde{c}_t + \hat{c}_t + \psi \delta p_{h,t} \hat{h}_t \tag{A.29}
\]

\[
M_t^c = M_t^b \tag{A.30}
\]

\[
B_t = B_t^c + B_t^b \tag{A.31}
\]