# The Calm Before the Storm: Time Varying Volatility and the Origins of Financial Crises

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JOB MARKET PAPER

December 2, 2014

**Abstract**

What causes financial crises? I show that shocks to the volatility of total factor productivity (TFP) can generate endogenous variations in loan-to-value (LTV) ratios and trigger credit crunches, without appealing to financial shocks. Using a panel of countries, I find that financial crises coincide with the reversal of a long period of low volatility of TFP. To explain this new fact, I develop a general equilibrium model in which volatility shocks to TFP interact with an occasionally binding borrowing constraint and housing serves as collateral. I introduce search frictions in the housing market to capture the liquidity of housing and endogenize the LTV ratio: households borrow at higher LTV ratios when the collateral is more liquid. In this environment, volatility shocks cause financial crises by changing the liquidity of the collateral. Periods of low volatility sow the seeds of the crisis by boosting housing liquidity and raising LTV ratios; then a sudden volatility spike freezes the liquidity of housing and reduces the LTV ratio, forcing households to sharply deleverage. In a quantitative exercise, I feed the model with the stochastic volatility of the U.S. Solow residual. I find that the interaction of volatility shocks and search frictions in the housing market increases the frequency of financial crises by 55%. In addition, volatility shocks generate volatile LTV ratios, thus providing a foundation for financial shocks.

**Key Words:** Housing Market, Collateral Liquidity, Search Frictions, Non-Linear Dynamics.

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# 1 Introduction

What causes financial crises? Major credit crunches are usually considered events which originate in the financial sector. In this paper, I show that shocks to the volatility of total factor productivity (TFP) can generate endogenous variations in loan-to-value (LTV) ratios and trigger financial crises, without appealing to financial shocks. My focus on volatility links to the financial instability hypothesis of Minsky (1992), which conjectures that long periods of low fluctuations can lead to a crisis. This is a phenomenon that Brunnermeier and Sannikov (2013) refer to as the volatility paradox: it is the calm that generates the storm.

I first establish in the data an association between the volatility of TFP and financial crises which is consistent with the volatility paradox. I build a panel of crises across countries and find that the volatility of TFP is around 12% below trend over the two years preceding a financial crisis, before jumping up. This rise in volatility leads the burst of the crisis.

To explain this new fact, I develop a general equilibrium model in which volatility shocks interact with an occasionally binding borrowing constraint and housing serves as collateral. I introduce search frictions in the housing market to capture the liquidity of housing and endogenize the maximum LTV ratio (i.e., the maximum amount households can borrow given the value of their assets). Households borrow at higher LTV ratios when the housing market is more liquid. In the model, financial crises happen when the LTV ratio drops and the borrowing constraint becomes binding, which forces households to deleverage. The constraint binds with a probability that depends on the optimal choices of the households.

In this environment, volatility shocks affect the frequency of credit crunches by changing the liquidity of the collateral. A long period of low volatility sows the seeds of the crisis by boosting housing liquidity, which raises both the LTV ratio and households' leverage; then a sudden volatility spike freezes out the liquidity of the housing market and reduces the LTV ratio, forcing households to sharply deleverage.

In a quantitative exercise, I feed the model with the stochastic volatility of the Solow residual of the U.S. economy, which I estimate by Bayesian techniques. I use global numerical methods to solve the model and preserve its non-linear dynamics. I find that the interaction of volatility shocks and search frictions in the housing market increases the frequency of financial crises by 55% and the associated output drop by 58%. I show that financial crises are characterized by deflationary spirals à la Fisher (1933) in both the house price *and* the LTV ratio, a novel mechanism which amplifies the severity of a downturn. The initial drop in the LTV ratio forces households to deleverage, generating a decline in both house prices and housing liquidity, which eventually decreases even further the LTV ratio in a deflationary loop. Furthermore, the model accounts for around half of the observed time variation in LTV ratios. Hence, the interaction of volatility shocks and search frictions in the housing market provides a rationale for financial shocks.

The mechanism of the paper works through changes in the liquidity of housing, which eventually modify the maximum LTV ratio at which households borrow. In the model, periods of low volatility boost housing investment. As more households look for a house, sellers are more likely to meet with a buyer. The higher liquidity of housing relaxes the LTV ratio and generates a credit and an investment boom which reinforce each other. This spiral builds up systemic risk because the economy becomes fragile to the realizations of adverse shocks at high levels of households' leverage. Indeed, the dynamics of the model are non-linear. As in Mendoza (2010), Bianchi (2012) and Bianchi and Mendoza (2013), negative shocks generate only mild recessions at low levels of leverage. Instead, when households are highly indebted, a sudden peak in volatility can dry up the liquidity of housing and lower the LTV ratio down to the point that the borrowing constraint becomes binding. Agents are then forced to deleverage and fire sell their houses, triggering a debt deflationary spiral in both the house price and LTV ratio, which turns the credit boom into a bust.

The search frictions in the housing market creates a direct link between the liquidity of the collateral and households' borrowing capacity, a novel mechanism in the literature of general equilibrium models with financial frictions. While standard models à la Kiyotaki and Moore (1997) usually assume that the LTV ratio is exogenous, in this paper the ratio is endogenous. The link between housing liquidity, collateral values and the LTV ratio follows Brunnermeier and Pedersen (2009), in which market liquidity directly determines households' funding liquidity, that is, the ease at which households can access new loans. More precisely, a house has a high collateral value if lenders can sell it both quickly and at a high price in case they seize it.[1] In equilibrium the LTV ratio is the ratio between the option value of a vacant house - the value of a house on sale that is expected to be sold in the future and does not yield any dividend or utility to its owner - and the market value of housing. The wedge between these two prices widens in illiquid markets because houses are expected to be on sale for a longer time. Through this channel, changes in the liquidity of the housing market alter the value of the collateral asset and affect households' borrowing capacity. From this perspective, this paper follows the contributions of Fostel and Geanakoplos (2008) and Geanakoplos (2010) on the importance of endogenizing the LTV ratio to match of the dynamics of macroeconomic and financial variables.

How can volatility affect housing investment? The volatility shocks propagate into the real economy through the frictional housing market. Indeed, search frictions generate adjustment costs and partial irreversibilities in housing investment. On the one hand, households incur search costs whenever they look for a house. On the other hand, agents sell their properties at a discounted price when the housing market is illiquid. Hence housing investment is expensive to reverse. As shown in Bloom (2009), in this environment agents become more cautious in uncertain times: agents reduce ex-ante their investment propensity to avoid incurring ex-post the costs of frequently adjusting the housing stock. In the quantitative analysis, I show that volatility shocks barely change the frequency of financial crises if there are no search frictions in housing market. Even in the case I consider a frictional housing market, volatility shocks matter only if households' LTV ratio is not constant and does depend on housing liquidity. From this point of view, this paper contributes to

[1]The role of the collateral liquidity is already pointed out in Del Negro et *al.* (2011) and Kiyotaki and Moore (2012). These papers exogenously impose the degree of collateral illiquidity, ruling out any feedback effect between market liquidity and households' funding liquidity.

the literature on the real effects of volatility shocks (e.g., Justiniano and Primiceri, 2008; Bloom, 2009; Fernandez-Villaverde et *al.*, 2011) on two dimensions. First, I find a new propagation mechanism for the volatility shocks: the interaction of search frictions in the market of the collateral asset and an endogenous LTV ratio. Second, I show that changes in the *exogenous volatility* of productivity may generate sharp movements in the *endogenous volatility* of output and credit when households' leverage is excessively high.[2]

The presence of the volatility shocks and its effect of house prices relates to Bansal and Yaron (2004), where the stochastic volatility of consumption growth accounts for the time variation of risk premia. The importance of aggregate volatility is also stressed in Bansal et *al.* (2014), who point out that macroeconomic volatility is a primary source of risk affecting asset prices. I complement this literature by showing that the introduction of a stochastic volatility in a production economy with CRRA preferences can generate sharp fluctuations in house prices around a financial crisis.

Finally, this paper provides a quantitative theory of financial crises which sheds lights on the debate on the causes of the last recession. For instance, Gilchrist and Zakrajsek (2012) and Jermann and Quadrini (2012) show that the recent crisis has been driven by a large negative financial shock that generated a credit crunch and consequently a sharp drop in investment and employment. These results have consolidated the view that the cause of the recent crisis is the disruption of *credit supply* due to the breakdown of banks.

Yet, this explanation is at odds with the empirical evidence provided by Mian and Sufi (2009, 2011), who find that the housing market in the U.S. started to slump around 2006, much earlier than the collapse of Bear Stearns and Lehman Brothers. In this vein, the deterioration of the balance sheet of the households - rather than the one of the financial intermediaries - has triggered the Great Recession.

[2] What is the interpretation of the volatility shocks? Carvalho and Gabaix (2013) show that the changes from the manufacturing sector towards the service and financial sector can account for the movements in the volatility of U.S. macroeconomic variables over the last decades. Alternatively, Bloom (2009) finds that time variations in aggregate volatility are correlated with changes in the cross-sectional dispersion of firms' growth rates. Christiano et *al.* (2014) shows that shocks to the dispersion of firms' productivity are a key source of business cycle fluctuations.

To reconcile these different views, I propose a mechanism which is only based on real shocks - especially on innovations to the volatility of TFP - and works entirely through variations in *credit demand*. In the model there is no bank. However, volatility shocks drive changes in housing liquidity, which affect households' collateral values and eventually modify the LTV ratio. This mechanism makes households' leverage to move over time even when the house price does not change. Hence, the interaction of volatility shocks and a frictional housing market generates dynamics in the LTV ratio that are observationally equivalent to a financial shock, although they entirely hinge on credit demand. This result suggests that financial shocks should not necessarily be interpreted as if they were originated in the financial sector, and could rather be caused by shifts in credit demand.

## 1.1 Related Literature

This paper is connected to three strands of literature. First, I complement the empirical evidence provided by Reinhart and Rogoff (2009), Mendoza and Terrones (2012), Schularick and Taylor (2012), and Jorda et *al.* (2013a,b) on the dynamics of macroeconomic variables around financial crises. These authors show that financial crises are actually credit booms gone bust. I document that although aggregate volatility does not display strong comovements with recessions, it is characterized by large swings around financial crises. Second, this paper contributes to the debate on the recent house price boom and bust. Global imbalances are often referred to as the main cause of the house price boom. For instance, Justiniano et *al.* (2014) show that the global savings glut accounts for around one fourth of the increase in U.S. house prices in the early 2000's. Yet, Favilukis et *al.* (2013) argue that the boom and bust in the housing market is explained by financial development in the mortgage market. While there is a burgeoning evidence on the improvements in financial markets in recent years, it is harder to understand the reversal of the process of financial development amidst the financial crisis. In my model movements in the LTV ratio - due to changes in housing liquidity - provide a rationale to both the process of financial development and its reversal.

The relaxation of credit conditions in the mortgage market can be explained by the high liquidity of the housing market in the 2000's. Analogously, the liquidity freeze around the crisis can account for the reversal of the process of financial development. Third, this paper relates to the literature on search frictions in the housing market, which follows the contribution of Wheaton (1990). For example, Diaz and Jerez (2013) show that a model with a frictional housing market can reproduce the house price volatility. I add to this literature by showing that changes in housing liquidity affect the frequency of financial crises.[3,4]

# 2 Evidence on Volatility and Financial Crises

In this Section I document a new stylized fact on the dynamics of the volatility of TFP around financial crises. I find that crises coincide with the reversal of a long period of low fluctuations. To shed light on this fact, I run a structural VAR to evaluate how volatility shocks propagate in the real economy through the housing market.

## 2.1 Data on Volatility and Financial Crises

I build a panel of 20 developed countries from 1980 until 2013 to understand how volatility is related to financial crises. The countries covered are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom and the United States. For any of these countries, I consider an indicator of aggregate volatility at an annual frequency: the stochastic volatility of total factor productivity (TFP). I compute the series of TFP $z_t$ for each country using data from the Penn World Tables. Then, I posit that in each country

[3] There is also a recent literature that studies the role of search frictions in over-the-counter financial markets building on Duffie et *al.* (2005, 2007). See Rocheteau and Weill (2011) for a review of this literature.

[4] The setting of the housing market in my paper follows Ungerer (2013), which shows that monetary policy affects aggregate leverage through a borrowing margin that depends on housing liquidity. Instead, I focus on the link between volatility, housing liquidity and financial crises, and emphasize the Fisherian deflation in LTV ratios amidst a crisis.

TFP follows a first-order autoregressive process with stochastic volatility

$$
\begin{aligned}
z_t &= \rho_z z_{t+1} + e^{\sigma_t}\epsilon_{z,t}, && \epsilon_{z,t} \sim N(0,1) \\
\sigma_t &= (1-\rho_\sigma)\bar{\sigma} + \rho_\sigma \sigma_{t-1} + \eta\epsilon_{\sigma,t}, && \epsilon_{\sigma,t} \sim N(0,1)
\end{aligned}
\tag{1}
$$

where $\rho_z$ denotes the persistency of the level equation of TFP, $\rho_\sigma$ is the persistency of the volatility equation, $\bar{\sigma}$ is the long-run mean of the volatility of TFP and $\eta$ captures the degree of stochastic volatility in the process. $\epsilon_{z,t}$ and $\epsilon_{\sigma,t}$ denote the innovations to the level and volatility of TFP, respectively. I assume that both $\epsilon_{z,t}$ and $\epsilon_{\sigma,t}$ are independent to each other.

Since the innovations $\epsilon_{z,t}$ and $\epsilon_{\sigma,t}$ are unknown to the econometrician, I need to apply a filter to the data to estimate the parameters of the process (1). In this framework the Kalman filter is unsuitable because it applies only to linear series, while here the shocks to the volatility enter non-linearly in the level equation of TFP. I evaluate the likelihood of this process by appealing to the Sequential Importance Sampling particle filter introduced in Fernandez-Villaverde and Rubio-Ramirez (2007) and Fernandez-Villaverde et *al.* (2011). The estimation of the stochastic volatility of TFP closely follows Born and Pfeifer (2013). I use Bayesian techniques to estimate the likelihood of the process of productivity. I elicit some unrestrictive priors, and after deriving the likelihood of the process for some given parameters with the SIS particle filter, I maximize the posterior likelihood using a random walk Metropolis-Hastings algorithm with 20000 replications, out of which the first 5000 represent burn-in draws. Finally, I recover the historical distribution of the volatility of TFP using the backward-smoothing routine of Godsill et *al.* (2004).[5]

I also consider different measures of volatility as robustness checks. First, following Bloom (2009), I proxy aggregate volatility with the logarithm of the variance of daily stock returns within a year. Second, I compute the volatility of quarterly GDP growth over a moving window of 20 quarters.

[5]I report the computational algorithm and the details on the priors in the Supplementary Appendix.

Finally, I take the dates of financial crises from multiple sources, that is, Bordo et *al.* (2001), Caprio and Klingebiel (2003), Reinhart and Rogoff (2009), Laeven and Valencia (2012), Schularick and Taylor (2012), Jorda et *al.* (2013b). Financial crises are defined as credit crunches in which the financial sector experiences large losses and bank runs, that eventually lead to a spike in bankruptcies, forced merged and government intervention. The dates of recessions are instead given by the OECD recession indicators. Overall, the panel covers 29 events of financial crises and 118 events of recessions. I report the dates of crises and recessions by country and all the sources of the data in Appendix A.

## 2.2 The Dynamics Around Crises and Recessions

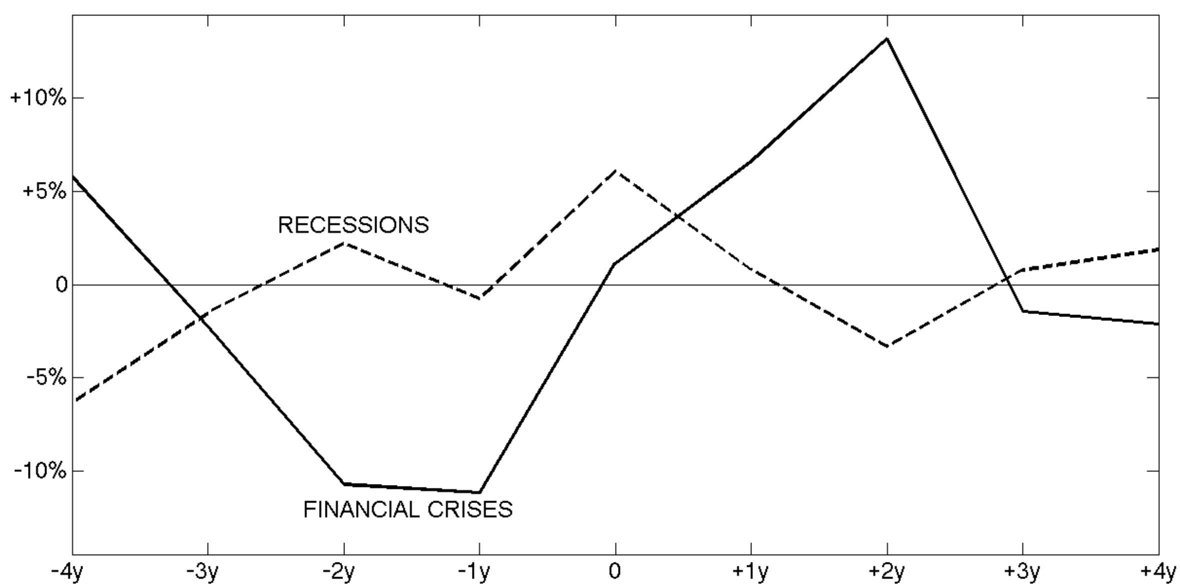
This Section studies the dynamics of volatility around financial crises and recessions. For any country and for any financial crisis and recession, I take the series of aggregate volatility in a time window of nine years around the event of interest, that is, from four years before either the financial crisis or the recession up to four years afterwards. Then, I consider the series defined by the average observations across events for any year of the window as the typical pattern around financial crises and recessions. For example, to define the typical level of volatility the year preceding a financial crisis, I take the volatility of the Solow residual one year before each of the 29 financial crises of my sample and then compute the mean.

Figure 1 displays the typical dynamics of aggregate volatility around financial crises and recessions. The figure documents that aggregate volatility asymmetrically varies around crises and recessions. While there are negligible deviations from trend during recessions, the behaviour of volatility around crises is characterized by large swings. Crises tend to be preceded by years in which volatility is around 10% below trend and the burst of the crisis pushes volatility up to around 13% above trend.

Figure 2 shows that aggregate volatility maintains the same dynamics around financial crises and recessions even when it is measured as the variance within a year of daily stock returns or when I use the variance of quarterly GDP growth rates over a moving window of 20 quarters. I also find a similar dynamics when either considering the median observations of the deviations of the Solow residual from trend around crises and recessions or ruling out the last financial crisis episodes, see Appendix B. The Supplementary Appendix provides panel data evidence showing that a low level of volatility predicts the burst of financial crises, even when controlling for other macroeconomic variables, country characteristics, and country and year fixed effects.[6]

I argue that this evidence points out a new stylized fact on the dynamics of volatility around financial crises which is consistent with the volatility paradox of Brunnermeier and Sannikov (2013).

Figure 1: Aggregate Volatility around Crises and Recessions.

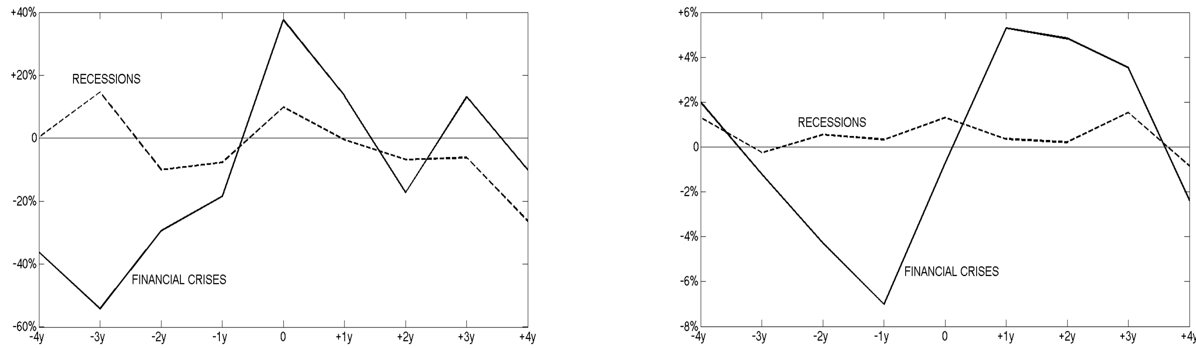



The figure plots the average values of the deviations from the trend of the stochastic volatility of countries' total factor productivity around recessions and financial crises (9 year window). The continuous line indicates the dynamics around financial crises, while the dashed line refers to recession. The dates of financial crises are taken from Reinhart and Rogoff (2009). Recessions are derived from the OECD recession indicators.

[6]Do volatility shocks cause financial crises? Figure 1 cannot identify whether the rise in the volatility of TFP causes the financial crisis or vice versa. Figure 2 shows that rises in aggregate volatility tends to lead the occurrence of financial crises. In Appendix B, I plot the VIX index amidst the Great Recession, and I show that the VIX rose by around 60% at the beginning of 2007, well before the burst of the crisis. This evidence supports the view that financial crises are led by a sudden peak in aggregate volatility.

Figure 2: Different Measures of Aggregate Volatility.

(a) Volatility of Stock Returns (b) Volatility of GDP Growth




Note: The figure plots the dynamics of different measures of aggregate volatility around recessions and financial crises (9 year window). In Panel (a) the volatility is measured as the variance of daily stock market returns within a year. In Panel (b) the volatility refers to the variance of quarterly GDP growth rates computed over a moving window of 20 quarters. The continuous line indicates the dynamics around financial crises, while the dashed line refers to recession. The dates of financial crises are taken from Reinhart and Rogoff (2009). Recessions are derived from the OECD recession indicators.

## 2.3 Volatility Shocks and the Housing Market

The previous analysis points out that changes in the level of aggregate volatility tend to coincide with the build-up of risk and the burst of a financial crisis. What is the mechanism behind this result? In this Section I show that volatility shocks are propagated into the real economy through the housing market. I run a structural VAR model, in which I compute the response of house price, the quantity of house sold and a measure of liquidity of housing to an unexpected increase in volatility.

The VAR is estimated using with monthly data from January 1963 until December 2013 on the level of S&P 500 returns, an indicator of volatility, the Federal Funds Rate, the consumer price index, industrial production and three variables on the housing markets related to price, quantity and liquidity.

I borrow the volatility indicator from Bloom (2009). This variable identifies a number of large and arguably exogenous peaks of stock market volatility, and is defined such that it equals 1 in each of these dates and zero otherwise. These dates coincide with events like the assassination of Kennedy, the Arab-Israeli War, the Gulf War and the 9/11 attack. The identification restriction posits that within a month the volatility indicator reacts only to the level of the S&P stock returns, but not to any of the aforementioned macroeconomic variable. The presence of the stock returns allows me to disentangle volatility shocks from any change in the level of stock market data. As housing market variables, I consider the median sales price of new one family homes sold[7], the number of new one family homes sold and the months supply provided by the Census Bureau. The latter is the ratio of houses for sale to houses sold and measures the number of months a house for sale is expected to last on the market. Hereafter I refer to this variable as the time on the market.

The benchmark ordering of the VAR considers the level of S&P 500 returns and the indicator of volatility first, then the interest rate, the consumer price index and the house price index, and finally the quantities with the industrial production, the level of sold houses and the time on the market. Figure 3 reports the response of house prices, the number of houses sold and the time on the market to a positive one standard deviation shock to volatility. Panel (b) shows that house prices respond very sluggishly to an increase in volatility, and start declining only around 10 months after the realization of the shock. At the peak, the response is around $-0.001\%$ below the baseline, which gives an annualized rate of $-1.21\%$. Instead, an increase in volatility reduces the number of houses sold at peak by around $-0.0065\%$ on a monthly basis, which gives an annualized rate of $-8.08\%$. Finally, a volatility shock raises the expected time on the market of a house in sale by $0.005\%$ on a monthly basis, which corresponds to an annualized rate of $6.17\%$. This evidence suggests that volatility shocks do affect the housing market, mostly through changes in the number of houses sold and the time on the market of a house on sale.

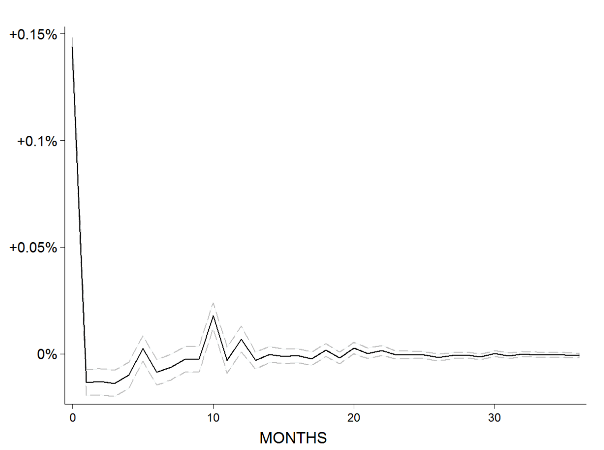
This evidence is consistent with the dynamics of GDP growth volatility and housing market liquidity over the last decades. Figure 4 shows that the volatility of GDP growth rates has decreased starting from the 1980's, a phenomenon which is known as the Great Moderation. Stock and Watson (2002) document that in those years the standard deviations of GDP, consumption and investment have decreased by 41%, 38% and 22%, respectively.

[7] Results do not change when using the Conventional Mortgage Home Price Index, see Appendix B.1.

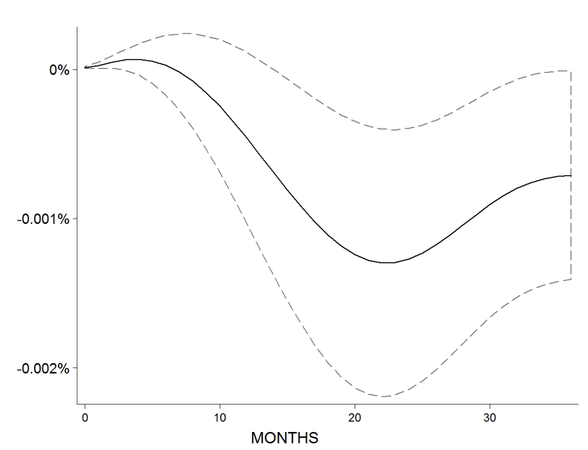
This trend has been partially reversed during the last recession. Figure 5 displays that the behavior of the housing market liquidity comoves with the volatility of the macroeconomic environment. Periods of low fluctuations experience a low time on the market, while turbulent periods - such as the oil crises in the 1970's and the Great Recession - have a much lower liquidity. Interestingly, the last period of the Great Moderation coincides with a historical low time on the market of a house of sale, at around 3.5 months. In the Great Recession, the time on the market peaked up to an all-time maximum of around 12 months.

Figure 3: Volatility Shocks and the Housing Market.

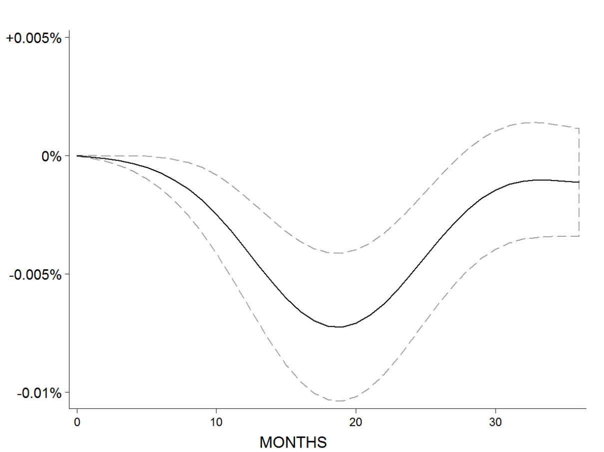
(a) Volatility



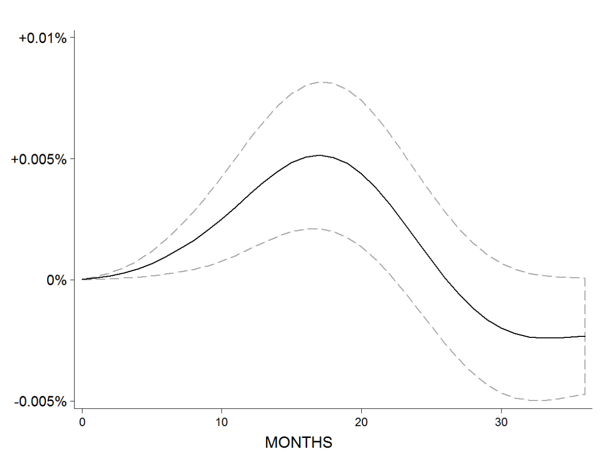

(b) House Price




(c) House Sales

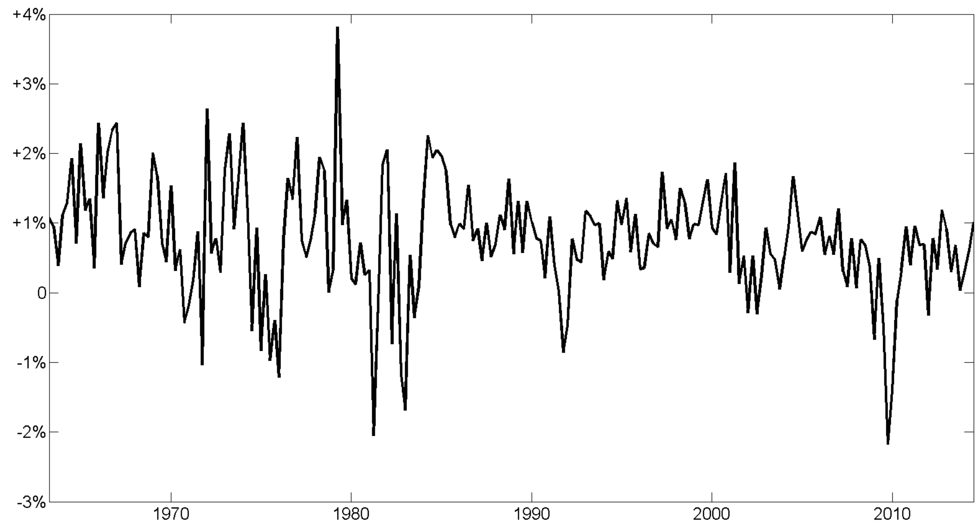



(d) Time on the Market



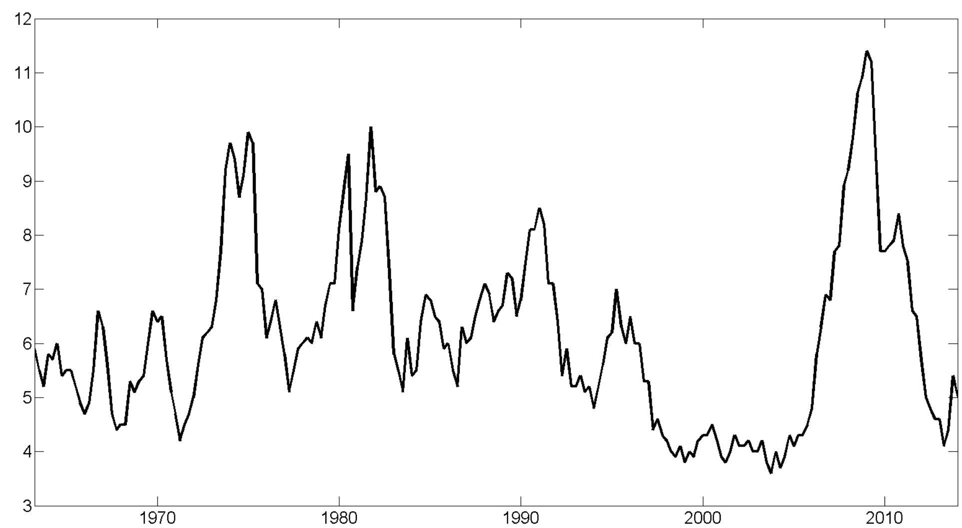

Note: VAR estimated from January 1963 to December 2013. The dashed lines are 1 standard-error bands around the response to a volatility shock. The coordinates indicate percent deviations from the baseline. The time on the market is measured by the monthly supply of homes, that is the ratio of houses for sale to houses sold.

Figure 4: U.S. GDP Growth Rate




Note: The figure plots the quarterly series of US GDP growth rate from 1970Q1 until 2013Q4. The series is computed as the first difference of the log real GDP.

Figure 5: Time on the Market of Houses on Sales in the U.S.




Note: The figure plots the quarterly series of the time on the market of houses on sale from 1963Q1 until 2013Q4. The time on the market series is given by the month supply of new one family houses from the Census Bureau.

# 3 The Model

## 3.1 Environment

In the economy there is a continuum of identical families that consist of a continuum of members. Although members live in different dwellings, there is perfect risk-sharing within the family. Families access a production function which assembles labor and housing to produce a consumption good. The technology is subject to aggregate productivity shocks with stochastic volatility.

Family members trade real estate properties on a frictional market, such that there is a probability that a house on sale will not be matched with a buyer.

Families borrow from foreign lenders, and lack of commitment to repay debt. If families renege on debt, lenders seize their housing stock. To avoid the repudiation of debt, lenders impose a constraint on families' borrowing capacity. In equilibrium, families cannot borrow more than the collateral value of housing.

The role of housing is threefold: it provides utility services, it is a production input and it acts as the collateral asset.

### 3.1.1 Timing

Every period is split into four different stages. In the first one families observe the current realizations of the shocks. In the second one families borrow from the foreign lenders. This stage serves as a rationale for having in equilibrium a borrowing constraint that depends on current values of families' collateral. In the third stage production takes place and family members trade real estate properties on a frictional housing market. Finally, in the fourth stage a fraction of homeowners is hit by a mismatch shock and forced to leave the houses, which become vacant.


## 3.2 Families

The economy is populated by a continuum of families $i \in [0, 1]$. Each family consists of a continuum of ex-ante identical infinitely-lived members of measure one. Each member lives in a different dwelling and can own at most one house. Although family members individually trade houses, they pool their revenues within the family.

Each family maximizes the sum of their members' life-time utilities

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U\big(c_{i,t}, l_{i,t}, h_{i,t+1}\big) \tag{2}$$

where $\beta$ is the time discount factor of family members, $c_{i,t}$ denotes the consumption of the family, $l_{i,t}$ is the level of leisure and $h_{i,t+1}$ is the end-of-period level of housing services which is assumed to be proportional to the end-of-period stock of occupied housing.

Families access a decreasing return to scale technology that uses labor force $n_{i,t}$, rented at the equilibrium wage $w_t$, and the stock of occupied housing $h_{i,t}$ to produce a homogeneous consumption good, as follows

$$y_{i,t} = e^{z_t} F\left(n_{i,t}, h_{i,t}\right). \tag{3}$$

The consumption good $y_{i,t}$ is sold on a frictionless market, and is the numeraire of the economy. The production function is subject to an aggregate productivity shock $z_t$, which follows an autoregressive motion with stochastic volatility

$$z_t = \rho_z z_{t-1} + e^{\sigma_t} \epsilon_{z,t} \tag{4}$$

$$\sigma_t = \left(1 - \rho_\sigma\right) \bar{\sigma} + \rho_\sigma \sigma_{t-1} + \eta \epsilon_{\sigma,t} \tag{5}$$

where $\rho_z$ denotes the persistence of the level of productivity, $\rho_\sigma$ is the persistence of the volatility of productivity, $\bar{\sigma}$ is the long-run mean of volatility and $\eta$ captures the degree of stochastic volatility of the process. When $\eta = 0$, the process reduces to a standard autoregression motion. Finally, $\epsilon_{z,t}$ and $\epsilon_{\sigma_t}$ denote the innovations to the level and volatility of productivity. I assume that they are i.i.d. following normal distributions $N(0, \sigma_{\epsilon_z})$ and $N(0, \sigma_{\epsilon_\sigma})$, respectively.

I appeal to this specification for aggregate productivity because the dynamics over time of the level and the volatility of aggregate productivity are pinned down by two different shocks, $\epsilon_{z,t}$ and $\epsilon_{\sigma,t}$, respectively. The two different sources of uncertainty, one related to the level and the other one linked to volatility, allows me to disentangle the role of volatility shocks and their contribution to the quantitative results of the model.[8]

## 3.3 The Housing Market

In the model houses are either occupied or vacant. Each family $i \in [0, 1]$ has a fraction of $h_{i,t}$ members which occupy a house and a fraction of $v_{i,t}$ members which own a house that does not fit their needs. I refer to the latter as vacant housing. I assume that vacant houses cannot be used as a production input, do not provide utility services and cannot be pledged as collateral. I further consider a fixed unit supply of houses.[9]

Real estate properties are traded on a frictional housing market. The search frictions capture in a reduced form the fact that matching in the housing market is time consuming. On one side of the market, each family has $v_{i,t}$ members who own vacant housing, which are put up on sale. On the other side of the market, there are $1 - h_{i,t}$ members which do not occupy a house and seek to buy one on the frictional market. Family members exercise a search effort $s_{i,t}$ - in units of time - in order to match with a seller. I assume that every unit

[8]E.g., in a GARCH model a unique shock drives the dynamics over time of both the level and the volatility of the process. I refer to Fernández-Villaverde et *al.* (2011) for further discussion on the topic.

[9]Davis and Heathcote (2007) find that the trend and volatility of US house prices are mostly driven by fluctuations in the price of land. Liu et *al.* (2013) show that fluctuations in land prices are a driving force of business cycle. In this vein, the housing stock in fixed supply of my model can be interpreted as land.

of search effort comes at a monetary cost $\kappa s_{i,t}^2$. The ratio between the total amount of buyers (measured in efficiency units) to the total supply of houses on sale defines the tightness of the housing market

$$\theta_t = \frac{\int_0^1 (1 - h_{i,t})\, s_{i,t}\, \mathrm{d}i}{\int_0^1 v_{i,t} \mathrm{d}i}. \tag{6}$$

A high market tightness $\theta_t$ indicates that the housing market is hot, that is, there are more buyers than sellers.

Following Wheaton (1990), the aggregate number of successful matches $m_t$ is defined by a constant return to scale Cobb-Douglas matching function

$$m_t = \left( \int_0^1 (1 - h_{i,t})\, s_{i,t}\, \mathrm{d}i \right)^{1-\gamma} \left( \int_0^1 v_{i,t} \mathrm{d}i \right)^{\gamma} \tag{7}$$

where $\gamma \in (0, 1)$. Upon a match, the transaction price of the house $q_t^{\mathrm{mkt}}$ is defined by a Nash bargaining problem, which I describe in Section 3.6. The matching function (7) stipulates that not all the houses supplied to the market are matched to a buyer. Indeed, the probability at which family members sell houses is

$$P_t^{\mathrm{sell}} = \frac{m_t}{\int_0^1 v_{i,t} \mathrm{d}i} = \theta_t^{1-\gamma}$$

which is increasing in the market tightness $\theta_t$. The probability at which family members meet with buyers raises in hot housing market because there is a disproportionately larger amount of buyers exerting a high effort. Instead, the probability that a family member meets with a seller equals

$$P_t^{\mathrm{buy}} = \frac{m_t}{\int_0^1 (1 - h_{i,t})\, s_{i,t}\, \mathrm{d}i} = \theta_t^{-\gamma}.$$

The probability of buying a house negatively depends on the tightness of the market. In a hot market, there are much more buyers than sellers, and any given family member is less likely to meet with a seller.

In this environment a family member manages to sell its house only with a probability $P_t^{\text{sell}}$. With the remaining probability $1 - P_t^{\text{sell}}$, the house keeps being on sale on the future period. Since vacant houses cannot be used either as production input and as collateral asset, I can define the option value of a house $q_t^{\text{opt}}$ - the value of a house on sale that does not yield any utility service or dividend to the owner - when the frictional market opens as

$$q_t^{\text{opt}} = P_t^{\text{sell}} q_t^{\text{mkt}} + \left(1 - P_t^{\text{sell}}\right) \mathbb{E}_t \left[\Lambda_{t+1} q_{t+1}^{\text{opt}}\right]. \tag{8}$$

Equation (8) stipulates that the option value of housing depends on the liquidity of the housing market, the housing price and the continuation value of a vacant house. On the one hand, vacant houses have no option value when their selling probability in any future period goes to zero. On the other hand, the option value of vacant houses equals the market value of houses - as priced by the frictional market - when the current frictional market is perfectly liquid, that is, $P_t^{\text{sell}} = 1$. Notice that the option value $q_t^{\text{opt}}$ is the actual value of houses put up on sale by the family members which sell their shelters. As long as the frictional market is partially illiquid, then $q_t^{\text{opt}} \leq q_t^{\text{mkt}}$, and the relevant house price for a seller is lower than the relevant house price for a buyer. Hence, the structure of the housing market endogenously generates a bid-ask spread $q_t^{\text{mkt}} - q_t^{\text{opt}}$ which depends on the liquidity of the frictional market.

Finally, I assume that a fraction $\psi$ of homeowners is hit by a mismatch shock after that trading in the housing market has taken place.[10] Sellers cease to occupy their own dwelling, which adds to the stock of vacant housing that is carried over the next period. The laws of

[10] The presence of the mismatch shock is often assumed in the literature of search frictions in the housing market, and dates back to Wheaton (1990). The shock allows to have always some vacant house in equilibrium. The mismatch shock can be interpreted by job mobility across locations, which forces homeowners to sell their real estate before relocating to a new city. Also a change in the number of people within a family could force homeowners to sell their house and buy a different one. The mismatch shock is analogous to the exogenous separation shock used in the search models of the labor market, see Pissarides (2000).

motion of occupied housing and vacant housing are

$$h_{i,t+1} = (1-\psi)\left(h_{i,t} + P_t^{\text{buy}} s_{i,t}\,(1-h_{i,t})\right) \tag{9}$$

$$v_{i,t+1} = \left(1-P_t^{\text{sell}}\right) v_{i,t} + \psi\left(h_{i,t} + P_t^{\text{buy}} s_{i,t}\,(1-h_{i,t})\right) \tag{10}$$

## 3.4 Borrowing Constraint

At the beginning of each period families observe the realizations of the aggregate shocks and then decide how much to borrow $d_{i,t+1}$. Families borrow from risk-neutral foreign investors, which inelastically supply funds at the gross interest rate $R$.[11] Families need also to purchase a fraction $\nu$ of the labor cost $w_t n_{i,t}$ in advance of production. Hence, they receive a working capital loan from the foreign investors. Working capital loans are repaid within the period and do not carry interest payments.

Families lack full commitment and can immediately decide to renege on their debt. In such a case, the lenders seize the housing stock $h_{i,t}$. Under the further assumptions that financial contracts are not exclusive, families can renege on their debt only at the beginning of each period and there is no additional penalty in repudiating the debt, Appendix D.1 shows that in equilibrium the collateral constraint equals

$$\frac{d_{i,t+1}}{R} + \nu w_t n_{i,t} \leq \underbrace{q_t^{\text{opt}} h_{i,t}}_{\text{Collateral Value of Housing}} . \tag{11}$$

As in Iacoviello (2005), families' borrowing capacity is determined by the collateral value of the housing. In Iacoviello (2005) the collateral value of housing equals to an exogenous fraction of its market value. In my model the collateral value of families' housing stock is always lower than its market value, as long as the housing market is not perfectly liquid, and there is a spread between the house price $q_t^{\text{mkt}}$ and the option value of a house $q_t^{\text{opt}}$.

[11] This assumption is consistent with the analysis of Mendoza and Quadrini (2009) and Warnock and Warnock (2009) on the effects of US foreign capital inflows on the Treasury bill interest rates since mid 1980's.

Multiplying and dividing the right-hand side of the constraint by the price of occupied housing $q_t^{\text{mkt}}$, the constraint becomes

$$\frac{d_{i,t+1}}{R} + \nu w_t n_{i,t} \leq \underbrace{\frac{q_t^{\text{opt}}}{q_t^{\text{mkt}}}}_{\text{Maximum Loan-to-Value Ratio}} \times \underbrace{q_t^{\text{mkt}} h_{i,t}}_{\text{Market Value of Housing}}. \tag{12}$$

Equation (12) shows that the collateral value of agents depends on the market value of their housing stock, multiplied by a factor which defines the maximum LTV ratio. Standard models usually assume that the degree of pledgeability of the collateral is an exogenous parameter. Instead, in this framework the LTV ratio is endogenous and depends on the liquidity of the housing market. When the housing market liquidity freezes out, the low probability of selling vacant houses raises the wedge between the prices of occupied housing $q_t^{\text{mkt}}$ and vacant housing $q_t^{\text{opt}}$. As a result, the LTV ratio $\frac{q_t^{\text{opt}}}{q_t^{\text{mkt}}}$ decreases. Therefore, Equation (12) defines the direct link through which the liquidity of the housing market endogenously determines agents' borrowing capacity. In this environment the LTV ratio moves over time because of the changes in the liquidity of the housing market.

## 3.5 Decentralized Equilibrium

The families use output net of the labor cost $z_t F(n_{i,t}, h_{i,t}) - n_{i,t} w_t$, the revenues from supplying labor $(1 - l_{i,t}) w_t$, the new amount of borrowing $\frac{d_{i,t+1}}{R}$ and the revenues from selling houses $q_t^{\text{mkt}} P_t^{\text{sell}} v_t$, to finance consumption $c_{i,t}$, the searching cost $\kappa s_{i,t}^2$, the repayment of debt $d_{i,t}$, and the purchases of new occupied houses $q_t^{\text{mkt}} P_t^{\text{buy}} s_{i,t}(1 - h_{i,t})$. Therefore, families' budget constraint reads

$$\begin{aligned} c_{i,t} + \kappa s_{i,t}^2 + q_t^{\text{mkt}} P_t^{\text{buy}} s_{i,t}(1 - h_{i,t}) + d_{i,t} = \left[e^{z_t} F(n_{i,t}, h_{i,t}) - n_{i,t} w_t\right] + \dots \\ \dots + (1 - l_{i,t}) w_t + q_t^{\text{mkt}} P_t^{\text{sell}} v_t + \frac{d_{i,t+1}}{R}. \end{aligned} \tag{13}$$

Hereafter, I focus on a symmetric competitive equilibrium. Since families are all ex-ante identical and there is no source of idiosyncratic uncertainty, families face the same budget and borrowing constraint, and take identical optimal choices. Therefore, I drop the subscripts from all the variables of the model.

The states of the families' problem are given by its stock of occupied houses $h_t$, the level of debt $d_t$, aggregate bond holdings $D_t$, the aggregate stock of occupied houses $H_t$ and finally the level and volatility of productivity, $z_t$ and $\sigma_t$. Since the stock of housing is in fixed supply, families do not need to take in account the stock of vacant houses $v_t$.

As long as prices depends on the aggregate level of bond holdings, and optimal decisions depend on current and future prices, families have to forecast also future aggregate bond holdings. I denote by $\Gamma_D(H, D, z, \sigma)$ the law of motion of aggregate bond holding $D$ perceived by any family, and $\Gamma_H(H, D, z, \sigma)$ is the law of motion of the aggregate stock of housing occupied by the families $H$. Then, the individual maximization problem is

$$V(h, d; H, D, z, \sigma) = \max_{c,l,n,s,d'} \left\{ U(c, l, h') + \beta \mathbb{E}_{z',\sigma'|z,\sigma} \left[ V(h', d'; H', D', z', \sigma') \right] \right\}$$

$$s.t. \quad c + d + C_h = e^z F(n, h) + \frac{d'}{R} + G_h \tag{14}$$

$$C_h = \kappa s^2 + q^{\text{mkt}}(H, D, z, \sigma) P^{\text{buy}}(H, D, z, \sigma) s(1-h) \tag{15}$$

$$G_h = q^{\text{mkt}}(H, D, z, \sigma) P^{\text{sell}}(H, D, z, \sigma) v \tag{16}$$

$$h' = (1-\psi)\Big(h + P^{\text{buy}}(H, D, z, \sigma) s(1-h)\Big) \tag{17}$$

$$\frac{d'}{R} + \nu w(H, D, z, \sigma) n \leq q^{\text{opt}}(H, D, z, \sigma) h \tag{18}$$

$$D' = \Gamma_D(H, D, z, \sigma) \tag{19}$$

$$H' = \Gamma_H(H, D, z, \sigma) \tag{20}$$

subject to the law of motion for the TFP shocks as described by Equation (4). Equation (14) denotes the budget constraint, Equation (15) defines the total cost of trading housing $C_h$, Equation (16) is instead the total gain from trading housing $G_h$, Equation (17) denotes the law of motion of occupied houses, Equation (18) is the borrowing constraint and Equations

(19) - (20) stipulate the perceived laws of motion for total bond holdings and occupied housing. Note that in the symmetric equilibrium $n_t = 1 - l_t$.

Upon observing the states of the economy, agents decide the optimal policy on consumption $\hat{c}\left(h, d; H, D, z, \sigma\right)$, working hours $\hat{n}\left(h, d; H, D, z, \sigma\right)$, the search effort in the housing market $\hat{s}\left(h, d; H, D, z, \sigma\right)$, and the amount of resources to borrow from the foreign investors $\hat{d'}\left(h, d; H, D, z, \sigma\right)$. In equilibrium, the perceived level of aggregate bond holdings $\Gamma_D\left(H, D, z, \sigma\right)$ has to coincide with the individual policy $\hat{d'}\left(h, d; H, D, z, \sigma\right)$, and the same applies for the law of motion of the aggregate stock of occupied housing $\Gamma_H\left(H, D, z, \sigma\right)$. Appendix C reports the definition of equilibrium and the first-order conditions of the problem.

## 3.6 Nash Bargaining

The price $q_t^{\text{mkt}}$ of an occupied house $h_{i,t}$ which is sold on the frictional market is determined through the following Nash bargaining problem

$$q_t^{\text{mkt}} \equiv \arg\max_{q_t^{\text{mkt}}} \left\{ S\left(q_t^{\text{mkt}}\right)^{\zeta} B\left(q_t^{\text{mkt}}\right)^{1-\zeta} \right\} \tag{21}$$

$$s.t. \quad S\left(q_t^{\text{mkt}}\right) = q_t^{\text{mkt}} - \mathbb{E}_t\left[\Lambda_{t+1} q_{t+1}^{\text{opt}}\right] \geq 0 \tag{22}$$

$$B\left(q_t^{\text{mkt}}\right) = V_t^H - q_t^{\text{mkt}} \geq 0 \tag{23}$$

where $S\left(q_t^{\text{mkt}}\right)$ is sellers' surplus in case of a transaction, $B\left(q_t^{\text{mkt}}\right)$ denotes buyers' surplus, $\zeta$ is sellers' bargaining power, and $V_t^H$ is the fundamental value that families attribute to a new unit of occupied housing. The expected future price of vacant houses is the outside opportunity for a family member that does not manage to sell its house.

In the symmetric competitive equilibrium each family has the same fundamental value of occupying a house and therefore the identity of the buyer does not matter on the specification of the house price. Indeed, in equilibrium the price of a occupied house is

$$q_t^{\text{mkt}} = \zeta V_t^H + (1-\zeta)\mathbb{E}_t\left[\Lambda_{t+1} q_{t+1}^{\text{opt}}\right]. \tag{24}$$

Families' fundamental value of housing can be derived using the envelope condition on the optimal stock of occupied housing, which yields

$$\begin{aligned} V_t^H =& \psi \mathbb{E}_t \left[ \Lambda_{t+1} \left( P_{t+1}^{\text{sell}} q_{t+1}^{\text{mkt}} + \left(1 - P_{t+1}^{\text{sell}}\right) q_{t+1}^{\text{opt}} \right) \right] + \dots \\ & \dots + (1-\psi)\, \mathbb{E}_t \left[ \Lambda_{t+1} \left( V_{t+1}^H + \frac{U_{h_{t+1}}}{U_{c_{t+1}}} + e^{z_{t+1}} F_{h_{t+1}} + \frac{\phi_{t+1}}{U_{c_{t+1}}} q_{t+1}^{\text{opt}} \right) \right] \end{aligned} \tag{25}$$

where $Y_{x_t}$ denote the derivatives of the function $Y(\cdot)$ with respect the term $x_t$ and $\phi_t$ is the Lagrange multiplier associated to the borrowing constraint. The fundamental value of a marginal house bought by a family member can be interpreted as follows. First, with probability $\psi$ the new homeowner is hit by the mismatch shock and forced to sell the house. The house is successfully matched with a buyer with a probability $P_{t+1}^{\text{sell}}$ and keeps being on sale with the remaining probability. If the family member is not hit by the mismatch shock, then she will effectively occupy the house over the following period. In this case, the family receives the utility service from occupying the house, uses the house as an input in the production function and gains the marginal productivity $e^{z_{t+1}} F_{h_{t+1}}$. Moreover, the family enjoys the continuation value of owning the house $V_{t+1}^H$. Finally, the ownership of an additional house increases the collateral value of families' housing stock, relaxing its borrowing constraint. Thereby, families can access a larger loan, increase consumption and raise its utility level by $\frac{\phi_{t+1}}{U_{c_{t+1}}} q_{t+1}^{\text{opt}}$.

## 3.7 Characterization of the Decentralized Equilibrium

**Proposition 1.** *In a steady-state equilibrium the LTV ratio* $\frac{q_t^{opt}}{q_t^{mkt}}$ *positively depends on the liquidity of the housing market. Proof. See Appendix D.2.*

In this model the LTV ratio is endogenous and depends on the liquidity of the housing market. When the market heats up, the ratio increases and therefore families' borrowing capacity increases. Analogously, a liquidity freeze tightens the LTV ratio, decreasing families' borrowing capacity. This result implies that the observed movements in maximum LTV ratios could be partially accounted for by changes in the liquidity of the housing market.

**Proposition 2.** *The house price $q_t^{mkt}$ negatively depends on the current shadow value of families' borrowing constraint. Proof. See Appendix D.3.*

When families become borrowing constrained, they decrease the level of search effort on the housing market generating a fire sale spiral which is detrimental for house prices $q_t^{\text{mkt}}$. In this environment fire sales negatively affect both families' collateral value and their LTV ratio, triggering a deflationary spiral in both the house price and the LTV ratio.

**Proposition 3.** *The tightness of the housing market equals family members' search effort.*

The behaviour of the frictional housing market is starkly simplified in a symmetric competitive equilibrium. Indeed, in this equilibrium every member opts for the same level of search effort, implying that $\int_0^1 (1-h_{i,t})\, s_{i,t} \mathrm{d}i = (1-h_t)\, s_t$. As a result, the equilibrium market tightness becomes

$$\theta_t = \frac{(1-h_t)\, s_t}{v_t} = s_t$$

since the total housing stock is an unitary fixed supply. The tightness of the housing market entirely depends on the search effort exerted by buyers. Hence, the housing market is hot as long as the level of effort is high. This result further implies that in each period the probability of selling a house is $P_t^{\text{sell}} = \theta_t^{1-\gamma} = s_t^{1-\gamma}$. Hot housing market are characterized by a high level of effort from buyers and a high probability of selling a house. The opposite applies in cold markets.

Instead, the probability of buying a house equals $P_t^{\text{buy}} = \theta_t^{-\gamma} = s_t^{-\gamma}$. Given this probability, the total amount of houses bought by a family member becomes $P_t^{\text{buy}} s_t\,(1-h_t) = s_t^{1-\gamma}\,(1-h_t)$, which is increasing in the level of search effort exerted by family members.

**Implication 1.** *The frictional housing market generates partial irreversibilities in housing investment.*

The price at which families purchase housing $q_t^{\text{mkt}}$ is higher than the expected price at which they sell houses $q_t^{\text{opt}}$. As in Duffie et *al.* (2005), the bid-ask spread depends on the presence of the search frictions. This spread implies that the housing investment is partial irreversible (i.e., the marginal gain of disinvestment is lower than the marginal cost of investment) and the degree of irreversibility fluctuates over time as a function of housing market liquidity. Investment is more irreversible in cold housing market.

**Implication 2.** *Partial irreversibilities in investment together with the presence of a decreasing to scale production function allow volatility shocks to have real effects: an increase in volatility freezes housing investment.*

Partial irreversibilities in investment coupled together with a decreasing return to scale production function make changes in volatility to have real effects. When it is expensive to reverse housing investment, family members become cautious and lower their search effort in uncertain times. Thus, a high volatility reduces the liquidity of the housing market. Instead, in a stable macroeconomic environment, agents increase their search effort and the housing market heats up. Decreasing returns to scale are key for this result. Caballero (1991) shows that a higher uncertainty decreases investment only in environment in which asymmetric adjustment costs interact with either imperfect competition or decreasing returns to scale technologies. If profits are convex in demand or costs, then a higher uncertainty actually rises expected profits leading to an investment boom.

# 4 Quantitative Analysis

I calibrate one period of the model to correspond to one quarter. To understand the quantitative relevance of the link between volatility, liquidity and financial crises, I estimate the shocks to both the level and the volatility of the aggregate total factor productivity of the U.S. economy using quarterly data from 1947Q2 until 2013Q4. The level and volatility shocks are estimated using Bayesian Sequential Monte Carlo methods.

I calibrate most of the parameters of the model to the values either estimated or used in previous papers. The main parameters which I calibrate to an empirical targets is the cost of searching effort in the housing market. Indeed, in Section 3.7 shows that the probabilities of buying and selling a house in the frictional market depend on the search effort exerted by the families. If the effort was costless, then the search frictions would be offset by an infinitely amount of search effort exerted by family members, and the liquidity of the housing market would be perfect. I calibrate the cost of search effort to match the long-run mean of the time on the market of a house on sale.

The model is solved numerically using global methods, which do not rely on approximations based on Taylor expansions around the steady state. Although the algorithm is much more time intensive, it preserves the non-linear dynamics of the model. I refer to the Supplementary Appendix for the details on the algorithm.

## 4.1 Estimating the Volatility of Total Factor Productivity

In the model the ultimate source of the build-up of risk and burst of financial crises is given by shocks to the level and the volatility of TFP. To understand the quantitative relevance of this mechanism, I take the actual series of level shocks and volatility shocks to TFP from the data. Namely, I derive the Solow residual of the economy using quarterly data on output, capital and labor from 1947Q2 until 2013Q4 and apply a one sided HP filter with parameter $\lambda = 1600$.[12] As in Section 2, I estimate the process using Bayesian methods. I elicit some unrestrictive priors, and after deriving the likelihood of the process for some given parameters with the Sequential Importance Sampling (SIS) particle filter introduced in Fernandez-Villaverde and Rubio-Ramirez (2007) and Fernandez-Villaverde et *al.* (2011), I maximize the posterior likelihood using a random walk Metropolis-Hastings algorithm with 25000 replications, out of which the first 5000 represent burn-in draws. Finally, I recover the historical distribution of the time varying volatility using the backward-smoothing routine of Godsill et *al.* (2004).

[12]The estimated series of Solow residual has to be considered just a proxy of the concept of productivity implied by my model. I refer to the Supplementary Appendix for further discussions on this issue and all the details on the computation of the Solow residual.

## 4.2 Estimation Results

I elicit Beta priors centred around 0.90 for both the autocorrelation coefficients of the level equation $\rho_z$ and the volatility equation $\rho_\sigma$. The implicit assumption is that both the level and the volatility are known to be highly persistent over time. For the degree of stochastic volatility $\eta$, I elicit a a Gamma prior with mean 0.315 and standard deviation 0.03 following the posterior estimate of Born and Pfeifer (2013), who derive the stochastic volatility of the U.S. Solow residual using data from 1970 on. Finally, I define a uniform distribution between $-11$ and $-3$ for the long-run log volatility $\bar{\sigma}$.

Table 1 reports the median, the 5-th and 95-th quantiles of the posterior distribution of each parameter. I find a strong persistence in both the level and volatility of TFP. The latter is very important because the mechanism of the model relies on the existence of a long period of low volatility which fosters a credit boom, and boosting households' leverage. The process is also characterized by a high degree of stochastic volatility. A one standard deviation increase in the volatility shocks raises the volatility of the innovation to the level of TFP by $(e^{\eta} - 1) \times 100 = 32.4\%$.

Table 1: Estimation of the Stochastic Volatility of TFP

| **Parameter** | **Prior** | | | **Posterior** | | |
|---|---|---|---|---|---|---|
| | Distribution | Mean | Std. Dev. | Median | 5 Percent | 95 Percent |
| $\rho_z$ | Beta | 0.90 | 0.10 | 0.8137 | 0.7500 | 0.8734 |
| $\rho_\sigma$ | Beta | 0.90 | 0.10 | 0.7949 | 0.6071 | 0.9065 |
| $\eta$ | Gamma | 0.315 | 0.03 | 0.2805 | 0.2362 | 0.3267 |
| $\bar{\sigma}$ | Uniform | -7.00 | 2.30 | -5.3869 | -5.5792 | -5.2130 |

Note: $\rho_z$ denotes the autocorrelation parameter of the level equation, while $\rho_\sigma$ is the autocorrelation of the volatility equation. $\eta$ captures the degree of stochastic volatility in the process, and $\bar{\sigma}$ denotes the long-run log volatility.

### 4.3 Calibration Exercise

Most of the parameters of the model are targeted to values estimated or used in previous papers. In particular, the calibration closely follows Bianchi and Mendoza (2013). The crucial parameter which is calibrated is the cost of exerting search effort on the housing market, which determines the behavior of the tightness of the market and eventually the level of housing liquidity.

I consider the following utility function for the families

$$U\left(c_t, l_t, h_{t+1}\right) = \frac{\left(c_t^{\xi} h_{t+1}^{1-\xi} - \mu \frac{(1-l_t)^{1+\omega}}{1+\omega}\right)^{1-\delta} - 1}{1-\delta}$$

The parameters $\delta$, $\mu$ and $\omega$ denote the risk aversion, the degree of disutility from working and the inverse of the Frisch elasticity of family members. The parameter $\xi$ governs the substitutability between consumption and housing.[13] This utility function belongs to the class of preferences introduced in Greenwood et *al.* (1988), and rules out any wealth effect on the labor supply, which would counter-factually lead to an increase in labor supply during a crisis. I set the disutility of work as $\mu = \alpha_n$ to have mean hours that equal 1. Then, the Frisch elasticity is defined as $1/\omega = 1$ and I set the risk aversion $\delta = 2$ as in Bianchi and Mendoza (2013), whereas $\xi = 0.76$ as in Davis and Ortalo-Magné (2011), who find that the share of households' expenditure in housing is constant over time around a value of 24%. The subjective time discount factor is set to the standard value at the quarterly frequency of $\beta = 0.99$.

I stipulate a decreasing return to scale production function

$$y_t = e^{z_t} n_t^{\alpha_n} h_t^{\alpha_h}$$

where $\alpha_n + \alpha_h < 1$. The parameter $\alpha_h$ is calibrated to match the ratio of housing stock value

[13]The Cobb-Douglas function in consumption expenditures reflects the fact that expenditure shares on housing are constant over time and across metropolitan areas, see Davis and Ortalo-Magné (2011).

over the GDP. Using data from the Flow of Funds from 1952Q1 until 2013Q4, the ratio of the market value of the real estate of the private nonfinancial sector over GDP is 2.24. In the model, this average is matched by a value of $\alpha_h = 0.11$. Instead, the labor share is set to the standard value of $\alpha_n = 0.64$. Overall, the returns to scale of the technology sum up to 0.75. Finally, the productivity process $z_t$ inherits the data generator process estimated in the previous Section.

I calibrate the gross real interest rate to $R = 1.0065$, that is the value that Bianchi and Mendoza (2013) estimate for the average of the ex-post real interest rate on three months Treasury Bills over the last three decades. Instead, the working capital coefficient is set to $\nu = 0.17$. To compute this value, I use firms' M1 money holdings to proxy for their working capital. Since two-thirds of the total M1 stock are held by firms, M1 accounts on average for 16% of annual GDP over the period 1959Q1-2013Q4, and the 0.64 labor share defined above, I set $\nu = 4 * (2/3) * 0.16/0.64 = 0.68$. Hence, firms maintain 68 percent of their quarterly wage bill in cash. This number is very close to the value of 0.63 used in Schmitt-Grohe and Uribe (2007).

Finally, I calibrate the parameters characterizing the dynamics of the housing market as follows. I define the mismatch shock to be equal to $\psi = 0.0278$ to match the average stay in a house of 9 years reported by Ngai and Tenreyro (2014). The parameter of the matching function which refers to the houses supplied to the market by the real estate sector is set to $\gamma = 0.21$ following the value estimated in Genesove and Han (2012). The bargaining power of the seller is set such as $\zeta = \gamma$ so that the Hosios (1990) condition holds. Finally, the monetary cost of exerting searching effort in the frictional market is calibrated to match the average time on the market of a house on sale using data from 1963Q1 until 2013, which is 6.21 months. In this way, I find a value of $\kappa = 0.67$.

Table 2: Calibrated Parameters

| **Parameter** | **Value** | **Target/Source** |
|---|---|---|
| Disutility from work | $\mu = \alpha_n$ | Normalization |
| Inverse Frisch elasticity | $\omega = 1$ | Bianchi and Mendoza (2013) |
| Substitutability consumption/housing | $\xi = 0.76$ | Davis and Ortalo-Magné (2011) |
| Risk aversion | $\delta = 2$ | Standard value |
| Time discount | $\beta = 0.99$ | Standard value |
| Share labor | $\alpha_n = 0.64$ | Standard value |
| Share housing | $\alpha_h = 0.11$ | Ratio real estate value over GDP=2.24 |
| Gross real interest rate | $R = 1.0065$ | Average return Treasury Bills |
| Working capital parameter | $\nu = 0.68$ | Ratio M1 over GDP held by firms |
| Mismatch shock | $\psi = 0.0278$ | Ngai and Tenreyro (2014) |
| Sellers' matching function parameter | $\gamma = 0.21$ | Genesove and Han (2012) |
| Sellers' bargaining power | $\zeta = \gamma$ | Hosios' condition |
| Cost searching effort | $\kappa = 0.67$ | Average TOM house on sale |

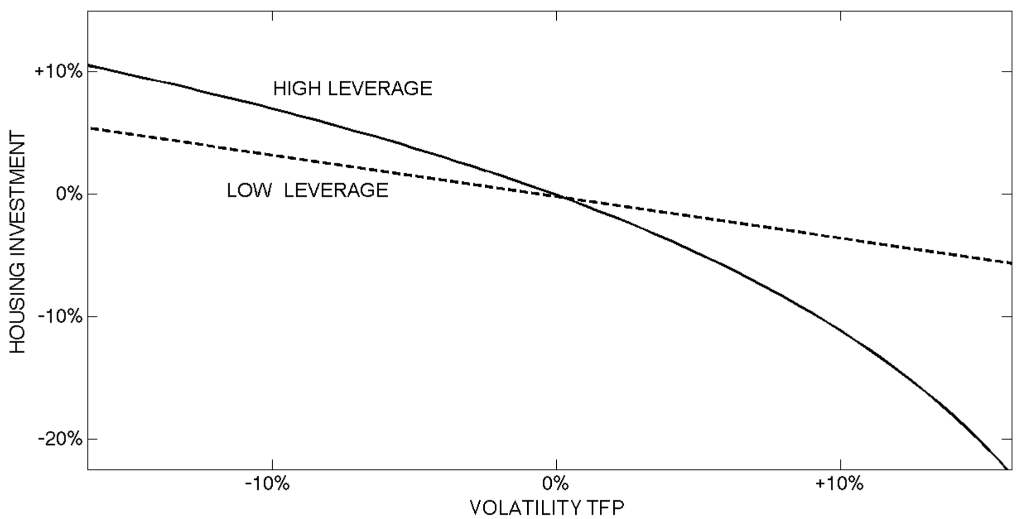
Note: The table report the calibrated value of all the parameters of the model, except for the DGP of the technology shock. TOM refers to the expected time on the market.

## 4.4 Quantitative Results

### 4.4.1 Real Effects of Volatility Shocks

How do volatility shocks affect the real economy? Figure 6 plots the policy function of housing investment (i.e., searching effort in the housing market) as a function of the volatility of TFP - at different levels of households' leverage. I report the values of both housing investment and TFP volatility as percentage deviations from their ergodic steady-state.

Figure 6: Policy Function of Housing Investment




The figure plots the policy function of housing investment (i.e., searching effort in the housing market) as a function of the volatility of TFP - for two different levels of households leverage, low and high. Housing investment and TFP volatility are defined as percentage deviations from the ergodic steady state.

Figure 6 shows that housing investment is decreasing in the level of TFP volatility. The higher the volatility, the more household members are discouraged to search for a house, the lower overall housing investment. Interestingly, the relationship between housing investment and TFP volatility does depend on households' leverage. When leverage is low, a 10% increase in the volatility of TFP reduces housing investment by around -3.5%. Instead, when households' leverage is high, the same change in volatility implies a fall in housing investment by around -7.5%. These differences are due to the fact that households' borrowing constraint is more likely to bind at high levels of leverage. When the constraint becomes binding, a small shock to productivity propagate much more into the real economy, because households have no additional borrowing capacity to smooth out the effects of shocks.

In addition, the relationship between housing investment and volatility becomes highly non-linear at high levels of leverage. Indeed, when leverage is high and volatility peaks, then the borrowing constraint becomes binding, which forces households to sharply reduce their debt and fire sell their housing stock.

### 4.4.2 Frequency and Severity of Financial Crises.

I compare the quantitative performance of five different economies with the data. In the first economy, which I refer to as the "RBC" case, I consider a standard model in which there are only level shocks to TFP and the housing market is perfectly liquid. In the second alternative, which I refer to as the "Search Frictions" economy, I add search frictions in the housing market in the "RBC" economy. This second case disentangles the role of search frictions alone in capturing the dynamics of financial crises. In the third case, which I refer to as the "Stochastic Volatility" economy, I add the volatility shocks to TFP to the "RBC" economy. Hence, this case disentangles the role of stochastic volatility once it is introduced in a standard framework with a perfectly liquid housing market. In the fourth and fifth economies I consider a "RBC" economy with *both* search frictions in the housing market and volatility shocks to TFP. The only difference between these two economies is that in the "Fixed LTV" economy I consider a constant LTV ratio at 100%, while in the "Stochastic LTV" economy I consider a LTV ratio which is endogenous and moves over time as a function of housing liquidity. These two economies disentangle the role of changes in the collateral liquidity as a propagation mechanism for the volatility shocks.

The addition of stochastic volatility - throughout the five economies - does not alter the unconditional mean of volatility. The presence of a stochastic volatility implies only a time varying pattern around the unconditional mean. The quantity of aggregate risk is the same in all the scenarios I compare.

Table 3 reports the results of the model on the frequency and the severity of financial crises, on a sample of simulated data over 10,000 periods. I compare the frequency and severity of financial crises implied by the five economies with the actual moments recovered from U.S. data. I define a financial crisis in the model as the state in which aggregate credit growth falls down by more than one standard deviation. According to this definition, over the last century there have been two financial crises: in 1929 and in 2007. As measures of severity, I consider the cumulative drop of output growth, employment drop and credit growth during the two years following a financial crisis (i.e, on the year upon the occurrence of the crisis and the following one).

Table 3: Results

| | **Data** | **RBC** | **Search Frictions** | **Stochastic Volatility** | **Search Frictions & Stochastic Volatility** | |
|---|---|---|---|---|---|---|
| | | | | | **Fixed LTV** | **Stochastic LTV** |
| Frequency Crises | 2.00% | 0.78% | 0.90% | 0.84% | 0.95% | 1.21% |
| Output Drop | −9.78% | −5.07% | −5.68% | −5.11% | −6.03% | −7.99% |
| Employment Drop | −10.29% | −4.20% | −4.96% | −4.37% | −5.14% | −6.03% |
| Credit Drop | −12.07% | −7.06% | −7.81% | −7.52% | −8.40% | −9.25% |

Note: The output drop, employment drop and credit drop refer to the fall in output growth, employment growth and credit growth over the two years following a financial crisis (i.e., upon the year of occurence and the following one). In the model, a financial crisis correspond to the state in which aggregate credit falls down by more than one standard deviation. The "RBC" refers to an economy with only level shocks to TFP and a perfectly liquid housing market. The "Search Frictions" refers to a RBC economy with a frictional housing market. The "Stochastic Volatility" refers to a RBC economy with stochastic volatility. The "Search Frictions & Stochastic Volatility" refers to a RBC economy with stochastic volatility and a frictional housing market. This economy is studied in two different cases. In the first one, "Fixed LTV", the LTV ratio is fixed at 100%. In the second one, "Stochastic LTV", the LTV ratio is endogenous and moves over time as a function of housing liquidity.

The second column of Table 3 shows that a standard RBC model generates too few and mild crises. This economy accounts for around 39% of the frequency of crises and 52% of the output drop. Introducing search frictions raises the probability of experiencing a financial crisis by 15% and the associated drop in output, employment and credit by 12%, 18% and 11%, respectively. Hence, changes in the liquidity of the collateral improve the performance of the model to a limited extent, when the ultimate source of exogenous variation is given by shocks to the level of TFP. Instead, if I consider the role of stochastic volatility of TFP into a standard RBC economy, the "Stochastic Volatility" case, I find that volatility shocks barely improves the predictions of the model. A time varying volatility amplifies the severity of crises just by 8%, while the drops in output, employment and credit hardly change. These results point out that volatility shocks need a propagation mechanism in order to have a relevant role in capturing the dynamics of credit crunches.

When I consider the benchmark economy with both search frictions and stochastic volatility of TFP, in which the LTV ratio is endogenous and moves over time as a function of liquidity (the "Search Frictions & Stochastic Volatility - Stochastic LTV" case), then the frequency of crises implied by the model raises to 1.21%, with an associated drop in output, employment and credit of -7.99%, -6.03% and -9.25%. Thus, the interaction of volatility shocks and search frictions in the housing market raises the probability of experiencing a crisis by around 55% with respect the basic RBC economy and accounts for around 60% of the observed frequency of crises. As far as the severity of the crisis is concerned, volatility shocks and search frictions boost the drops of output in employment by around 58% and 44%, and the fall in credit by 31%.

The results of the "Search Frictions & Stochastic Volatility - Fixed LTV" disentangle the contribution of the changes in the collateral liquidity on the performance of the model. When the LTV ratio is kept constant at 100%, then the predictions of the model worsens, both in terms of frequency and severity of crises. The comparison between the "Fixed LTV" and "Stochastic LTV" economies shows that changes in the liquidity of the collateral accounts for most of the increase in the frequency of financial crises of the benchmark economy.

These results point out that either search frictions or volatility shocks can improve the performance of the model, although falling short in capturing the characteristics of crises as in the data. The interaction of a frictional housing market and volatility shocks accounts for half of the probability of experiencing a crisis, and its corresponding drop in output and credit. The changes in the liquidity of the collateral, that eventually modifies the LTV ratio, represent the key mechanism through which volatility shocks propagate into the real economy. This finding adds to the literature on the real effects of volatility shocks, such as Justiniano and Primiceri (2008), Bloom (2009) and Fernandez-Villaverde et *al.* (2011), by pointing out that search frictions in the housing market amplifies the effects of the changes in volatility.

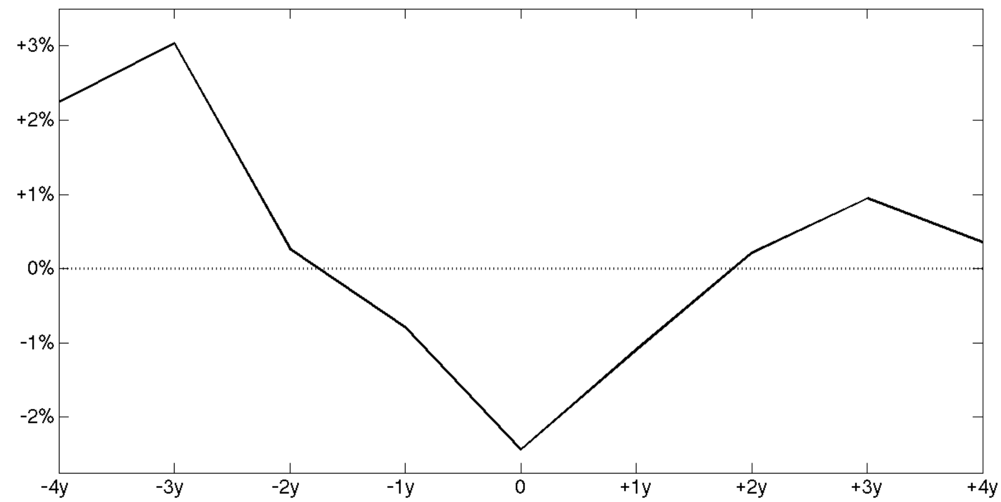
### 4.4.3 Dynamics of Aggregate Productivity around Financial Crises.

Table 3 shows that the volatility shocks to aggregate productivity raises the occurrence of financial crises by around 55%. What is then the dynamics of these shocks around financial crises? Figure 7 plots the behavior of the level and volatility of TFP around a crisis, as implied by the model.

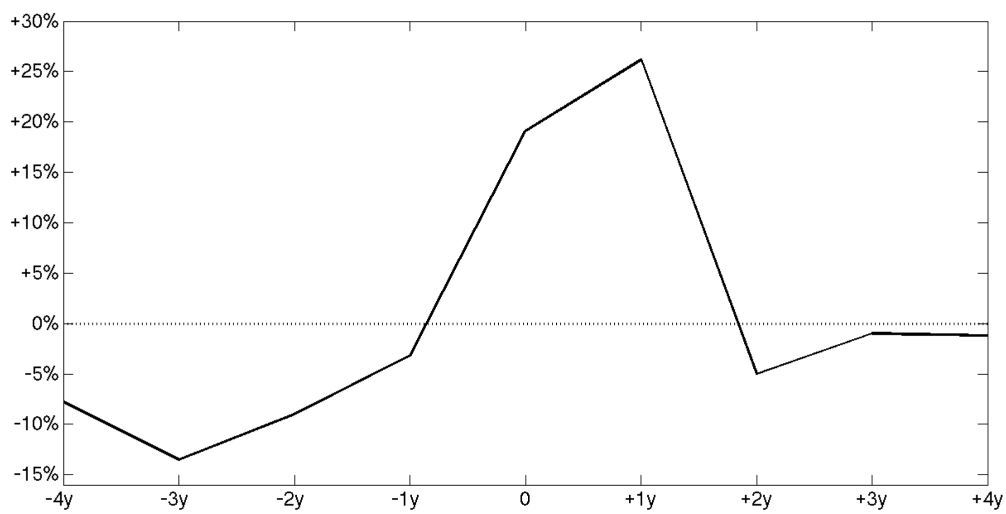
The graphs show that the period preceding a crisis is characterized by a high level and a low volatility of productivity. In the model, a financial crisis bursts after a long period of expansion in the economic activity. For example, the level of productivity is 3% above its long-run mean three years before a crisis, while the volatility of productivity is around 15% below mean. This long period of high level of productivity with low volatility generates a credit and investment boom which reinforce each other, raising the equilibrium LTV ratio and ultimately boosting households' leverage. In this way, these realizations of high productivity and low volatility builds up systemic risk. Indeed, a joint 2.5% drop in the level of productivity and a rise in volatility of around 27% turn the borrowing constraint into binding and trigger a crisis. Hence, a crisis coincides with both a slump in the level of productivity and a sudden spike in volatility which follow a long period of high productivity with low volatility.

Figure 7: Dynamics of Aggregate Volatility around Financial Crises.

(a) Level of Aggregate Productivity




(b) Volatility of Aggregate Productivity

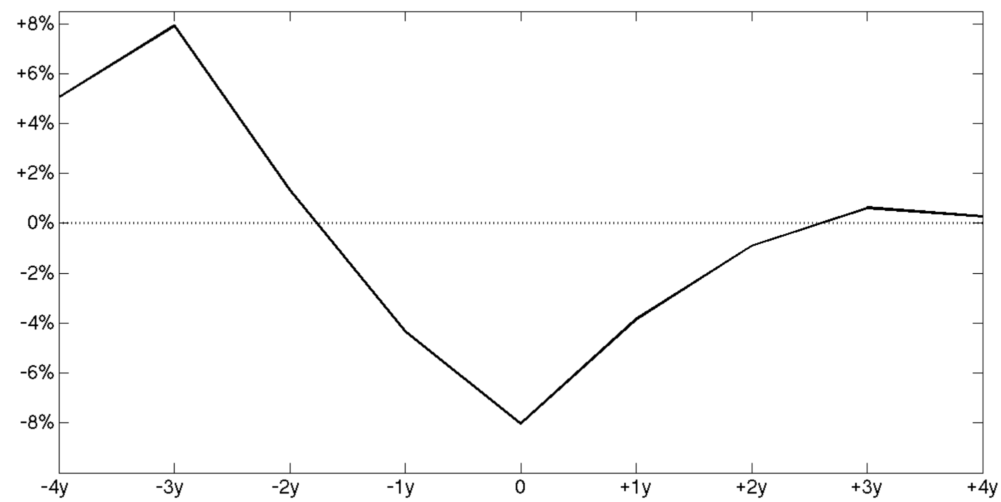



Note: The figure plots the average values of the deviations from the long-run mean of the level $z_t$ (Panel a) and the volatility $\sigma_t$ (Panel b) of total factor productivity in a 9 year window around financial crises. The solid line denotes the dynamics implied by the benchmark model, whereas the dashed line denotes the dynamics in the data. A financial crisis is defined as the state in which aggregate credit growth drops down by more than one standard deviation.

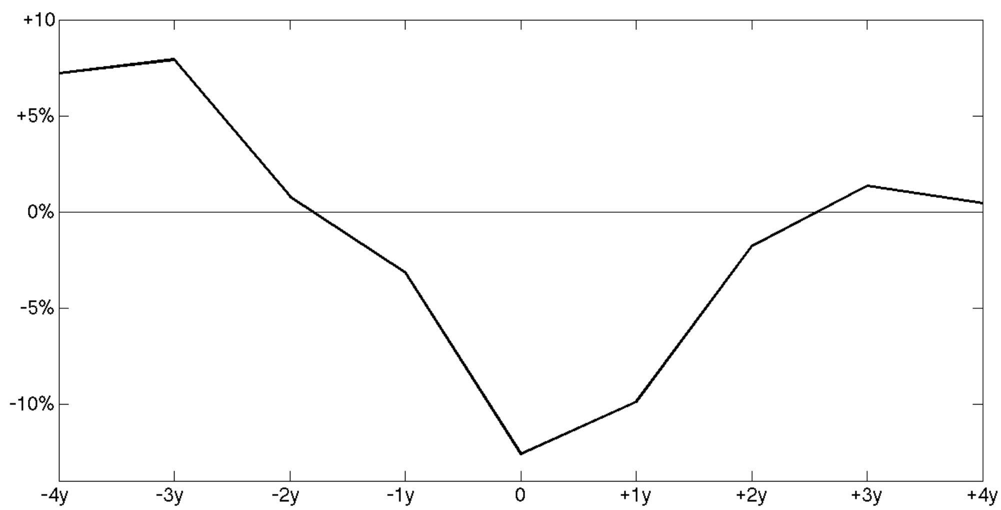
To understand the role of the changes in households' collateral values, I plot the dynamics of house price and the LTV ratio around financial crises in Figure 8.

Figure 8: House Price and Loan-to-Value Ratio around Financial Crises.

(a) House Price




(b) Loan-to-Value Ratio




Note: The figure plots the average values of the deviations from the long-run mean of the house price $q_t^{\mathrm{mkt}}$ (Panel a) and the loan-to-value ratio $\frac{q_t^{\mathrm{mkt}}}{q_t^{\mathrm{opt}}}$ (Panel b) in a 9 year window around financial crises. The solid line denotes the dynamics implied by the benchmark model, whereas the dashed line denotes the dynamics in the data. A financial crisis is defined as the state in which aggregate credit growth drops down by more than one standard deviation.

Figure 8 shows that financial crises are preceded by an inflationary spiral in both the house prices and the LTV ratio which relaxes households' credit limit and raises the level of leverage and therefore systemic risk in the economy. Afterwards, the inflationary spirals are abruptly reversed into deflationary spirals amidst the burst of the financial crisis.

In the model a financial crisis is preceded by a boom in house price of around 8% above mean, which is then turned into a house price bust at 8% below trend. A similar dynamics characterizes the LTV ratio. The ratio ranges around is 8% above mean before a financial crisis and it then turned into a very large drop, down to 13% below mean. So, amidst the financial crisis house price collapses by around 16% while the LTV ratio drops down by a larger extent, around 21%. This result underlies the key role of the novel mechanism of this paper - the endogenous boom and bust in the LTV ratio - in accounting for the frequency and the severity of financial crises.

In addition, the behavior of aggregate credit around crises can be used to compare the prediction of my theory with competitive explanations. Indeed, a rare disaster shock as in Barro (2006) and Gourio (2012) is able to generate a financial crises in which both output and credit significantly drop. Yet, such a theory could not explain the period of credit and output boom which precedes a financial crisis. From this perspective, a model with volatility shocks can generate both the upside risk and the downside risk that is necessary to account for the very nature of financial crises: credit booms which turn into bust.

#### 4.4.4 Time Variation in the Loan-to-Value Ratio.

In this Section I study the time variation in the LTV ratio $\frac{q_t^{\text{opt}}}{q_t^{\text{mkt}}}$ implied by the model. Table 4 reports the standard deviation of the LTV ratio in the data and in the four economies I consider. I report the average standard deviation of the LTV ratio together with the standard deviations conditional on whether the economies is in normal times or in crisis times. To derive the data counterpart of the LTV ratio of my model, I follow Jermann and Quadrini (2012). First, I log-linearize the collateral constraint defined in Equation (12). I assume that the collateral constraint is always binding and derive the series of the LTV ratio as the residual once I substitute each variable with its observable counterpart in the data. I take data on employment, wage, total liabilities and the market value of real estate. In this way, I obtain the value of the LTV ratio over time, a series which Jermann and Quadrini (2012) refer to as an exogenous financial shock.[14]

Table 4: Standard Deviation LTV Ratio

| | **Data** | **RBC** | **Search Frictions** | **Stochastic Volatility** | **Search Frictions & Stochastic Volatility** | |
|---|---|---|---|---|---|---|
| | | | | | **Fixed LTV** | **Stochastic LTV** |
| Average | 3.48% | 0% | 1.22% | 0% | 0% | 1.95% |
| Normal Times | 3.41% | 0% | 1.01% | 0% | 0% | 1.50% |
| Crisis Times | 5.52% | 0% | 3.23% | 0% | 0% | 4.25% |

Note: The LTV ratio is the ratio between the option value and the actual price of housing, $\frac{q_t^{\text{opt}}}{q_t^{\text{mkt}}}$. In the model, "Crisis Times" correspond to the states in which aggregate credit falls growth drops by more than one standard deviation. The "RBC" refers to an economy with only level shocks to TFP and a perfectly liquid housing market. The "Search Frictions" refers to a RBC economy with a frictional housing market. The "Stochastic Volatility" refers to a RBC economy with stochastic volatility. The "Search Frictions & Stochastic Volatility" refers to a RBC economy with stochastic volatility and a frictional housing market. This economy is studied in two different cases. In the first one, "Fixed LTV", the LTV ratio is fixed at 100%. In the second one, "Stochastic LTV", the LTV ratio is endogenous and moves over time as a function of housing liquidity.

Table 4 shows that as long as in the model the housing market is perfectly liquid and $q_t^{\text{opt}}$ equals $q_t^{\text{mkt}}$, the LTV ratio is constant and equals 1. This is case in all the economies without search frictions. Also in the economy with a fixed LTV ratio the standard deviation is zero by construction. Instead, the LTV ratio changes over time once I allow for a frictional housing market. In the "Search Frictions" economy, the standard deviation of the ratio is

[14]The standard deviation of the series does not change if either I consider only the data on real estate and liabilities of the household sector or I consolidate it with with the non-financial business sector.

1.22%. It equals 1.01% in normal times and it peaks up to 3.23% in crisis times. When I add volatility shocks, the standard deviation becomes 1.91%, with a value of 1.50% in normal times and 4.25% in crisis times. These results show that volatility shocks amplify the variation in the borrowing margin by around 60% on average, and account for 56% of the observed standard deviation of the borrowing margin. Moreover, Table 4 shows that although the model falls short in accounting for the volatility of LTV ratios in normal times, it provides a much better approximations in crisis times. The benchmark model accounts for around 77% of the standard deviation of LTV ratios amidst a financial crisis. Indeed, volatility shocks do not generate much variation in LTV ratios in good times. Instead, when the households' borrowing constraint becomes binding, changes in the level and volatility of TFP trigger a Fisherian deflation spiral in the house price and housing liquidity which amplifies the fluctuations in the LTV ratio.

Overall Table 4 shows that volatility shocks can be accounted for as a possible foundation of the financial shocks à la Jermann and Quadrini (2012), especially in crisis times. Hence, this model provides a quantitative theory of time varying LTV ratios which can be tested using data on housing market liquidity.

Moreover, in the model the changes in LTV ratios are driven by credit demand motives, because is no role for credit supply in the form of banks. The implications of this result are twofold. First, this evidence suggests that financial shocks should not necessarily be interpreted as if they were originated in the financial sector. Second, the findings of this paper can help reconciling different views on the cause of the last recession. Through the lenses of this paper, the fact the drop in investment, credit and employment amidst the Great Recession can be accounted for by a large negative financial shock - as shown in Jermann and Quadrini (2012) and Gilchrist and Zakrajsek (2012) - is not necessarily counterfactual with the possibility that the credit crunch was triggered by a fall in credit demand due to the deterioration of households' balance sheets, as shown by Mian and Sufi (2009, 2011).

### 4.4.5 Asset Pricing Implications

What are the characteristics of asset prices implied by the model? Table 5 reports the equity premium, the market price of risk and the Sharpe ratio associated with the investment in housing in the five different economies.

Table 5: Asset Prices

| | **RBC** | **Search Frictions** | **Stochastic Volatility** | **Search Frictions & Stochastic Volatility** | |
|---|---|---|---|---|---|
| | | | | **Fixed LTV** | **Stochastic LTV** |
| a. Unconditional | | | | | |
| Equity Premium | 0.65% | 0.72% | 0.67% | 0.88% | 1.14% |
| Market Price of Risk | 1.65% | 1.93% | 1.73% | 2.31% | 2.50% |
| Sharpe Ratio | 0.15 | 0.21 | 0.16 | 0.23 | 0.28 |
| b. Crisis Times | | | | | |
| Equity Premium | 10.59% | 10.96% | 10.79% | 11.63% | 12.51% |
| Market Price of Risk | 3.97% | 4.17% | 4.02% | 4.60% | 4.93% |
| Sharpe Ratio | 0.34 | 0.46 | 0.38 | 0.50 | 0.57 |

Note: The "Equity Premium" refers to the difference between the return on housing and the fixed risk-free interest rate. The "Market Price of Risk" is the ratio between the unconditional standard deviation and the unconditional average of the stochastic discount factor of the family. The "Sharpe Ratio" denotes the ratio between unconditional average and the unconditional standard deviation of the excess return. "Unconditional" denotes the moments of the model average over all the states of nature. "Crisis Times refer to the states in which aggregate credit growth drops by more than one standard deviation. The "RBC" refers to an economy with only level shocks to TFP and a perfectly liquid housing market. The "Search Frictions" refers to a RBC economy with a frictional housing market. The "Stochastic Volatility" refers to a RBC economy with stochastic volatility. The "Search Frictions & Stochastic Volatility" refers to a RBC economy with stochastic volatility and a frictional housing market. This economy is studied in two different cases. In the first one, "Fixed LTV", the LTV ratio is fixed at 100%. In the second one, "Stochastic LTV", the LTV ratio is endogenous and moves over time as a function of housing liquidity.

Table 5 shows that overall the behavior of asset prices starkly differs across normal times and financial crises. The unconditional equity premium is very low in all the different economies, ranging from the 0.65% of the "RBC" model up to the 1.14% of the benchmark model. Instead, upon the realization of a financial crises, the premium skyrockets up to 10.59% in the "RBC" economy and an even higher 12.51% under the benchmark economy. The same applies for the market prices of risk and the Sharpe ratio. For instance, the Sharpe ratio of the economy with search frictions in the housing market, stochastic volatility and stochastic LTV ratio is 0.28 unconditionally, and gets up to 0.57 amidst the occurrence of a financial crisis.

The asset pricing implications of the mode are then twofold. First, as in Bianchi and Mendoza (2013) and He and Krishnamurthy (2010), the non-linearities implied by the occasionally-binding borrowing constraint generate asymmetric movements in asset prices, which depend on whether the economy is experiencing a financial crisis. Second, the rare events in which the economy experiences a major drop in aggregate credit and a sharp rise in the excess returns help increasing the overall unconditional predictions of the model in terms of asset prices. Although the model still falls short in accounting for asset prices unconditionally, it is able to generate an excess return as high as 1.14% in the benchmark version.

Finally, Table 5 confirms that the search frictions in the housing market and especially the stochastic LTV ratio which depends on housing liquidity are important propagation channels of the TFP shocks. Indeed, the search frictions in the housing market increase the excess return by around 11%, while the interactions of search frictions and stochastic volatility further raises the excess return by around 58%. Importantly, the stochastic LTV ratio accounts for almost 23% of the overall unconditional equity premium. I deem the results to be an important contribution in and of itself: the interaction between funding liquidity and market liquidity is an important channel that could help standard production economies in accounting for the characteristics of asset prices.

# 5 Concluding Remarks

In this paper I show that financial crises - i.e., major credit crunches - can be triggered by real shocks. I consider a model where the exogenous source of variation is given by shocks to both the level and the volatility of TFP. In particular, I emphasize the role of shocks to the volatility of TFP as a source of financial instability, which generates periods of credit booms followed by deep busts.

The main propagation mechanism I propose is the presence of search frictions in the housing market. I show that in this environment the volatility shocks are propagated into the real economy by the liquidity of housing, which in the model is captured by search frictions. Moreover, as long as houses serve as collateral assets, the liquidity of the housing market determines households' maximum LTV ratio. LTV ratio can then be interpreted as liquidity discounts: households can access to a higher LTV ratio when the housing market is more liquid.

Search frictions in the housing market are crucial to let volatility shocks directly affect households' investment propensity in housing. In my model, the search frictions determine both partial irreversibilities (i.e., there is an endogenous bid-ask spread between the relevant house price of sellers and buyers) and adjustment costs in housing investment. Since housing investment is expensive to reverse, agents prefer a wait-and-see behavior in times of high uncertainty, which is eventually reflected in a lower investment. Therefore, changes in volatility drive the level of investment, and the higher the volatility, the lower the housing investment, the lower both the housing liquidity and households' LTV ratio.

Interestingly, in the model financial crises are characterized by deflationary spirals in both the house price and the LTV ratio, a novel mechanism which amplifies the magnitude of the credit crunch. These dynamics do not hinge on the presence of a financial sector: both the credit boom and the credit bust are entirely driven by changes in households' credit demand. Yet, the model generates dynamics in the LTV ratios which are observationally equivalent to a financial shock à la Jermann and Quadrini (2012). This evidence supports the findings of Mian and Sufi (2009, 2011), who point out that the deterioration of the balance sheet of the households, rather than the one of the financial intermediaries, has triggered the Great Recession.

The policy implications of this paper are twofold. First, these results warn policy-makers in interpreting shifts in LTV ratios as entirely driven by changes in credit supply. Hence, a financial shock is not a smoking gun supporting the government intervention in the financial sector. Second, the liquidity of housing - rather than the house price - is the relevant variable that captures the condition of the housing cycle. In a companion paper, Rachedi (2014), I provide evidence showing that the liquidity crunch in 2005 predicts the fall in house prices and households' leverage during the Great Recession.

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# A Data

## A.1 Aggregate Volatility and Financial Crises

I build a panel of 20 developed countries from 1980 until 2013. Extending the panel back to the 60's or 70's does not alter the results because in those years the 20 developed countries under investigation experienced almost no financial crisis. The countries covered are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom and the United States.

**Financial Crises:** I take the dates of financial crises from multiple sources, that is, Bordo et *al.* (2001), Caprio and Klingebiel (2003), Reinhart and Rogoff (2009), Laeven and Valencia (2012), Schularick and Taylor (2012), Jorda et *al.* (2013b). Financial crises are defined as credit crunches in which the financial sector experiences large losses and bank runs, that eventually lead to a spike in bankruptcies, forced merged and government intervention. I follow most of the dating procedure used in Schularick and Taylor (2012) and Jorda et *al.* (2013b).

**Recessions:** The dates of recessions are instead given by the OECD recession indicators. For the United States, I follow the dates provided by NBER. The dates of crises and recessions by country are reported in Table A.1.

**Total Factor Productivity:** I take the series of TFP from the Penn World Tables 8.0. TFP is computed as the residual of real GDP minus the capital stock times the complement to one of the share of labour compensation on GDP minus the total level of labor force (employment times average annual hours worked by persons engaged) multiplied by the share of labour compensation. The nominal variables are normalised at constant 2005 national prices.

**Stock Market Volatility:** The measure of aggregate volatility is based on the volatility of stock market returns. For each of the 20 countries of the panel, I consider the representative stock market index, I take daily returns and compute a measure of dispersion (either the variance or the interquantile range) within a period (either a year or a quarter). The stock market indexes are the following: MSCI for Australia, MSCI for Austria, MSCI for Belgium, TSX for Canada, MSCI for Denmark, MSCI for Finland, MSCI for France, DAX for Germany, ATHEX for Greece, MSCI for Ireland, MSCI for Italy, NIKKEI for Japan, MSCI for Netherlands, MSCI for Norway, MSCI for

Portugal, MSCI for Spain, MSCI for Sweden, MSCI for Switzerland, FTSE for the UK, DJIA for the US. The source of the data is Datastream.

**Credit to the Private Nonfinancial Sector:** I take the series on private credit from the "Long Series on Total Credit and Domestic Bank Credit to the Private Nonfinancial Sector" of the Bank for International Settlements. For each country, I take the adjusted for breaks nominal quarterly series. I take the series in which the lending sector is any sector and the borrowing sector is the private nonfinancial sector. Real values are derived by dividing the credit series by the CPI. Annual observations are computed by averaging the quarterly values within a year.

**Gross Domestic Product:** I take the series of real GDP for the United States from the Bureau of Economic Analysis, series ID *GDPC1*. For all the other countries, I take the series of nominal GDP from the "Main Economic Indicators" database of the OECD. I compute the real series by dividing the nominal GDP series by the CPI.

**House Prices:** Real house prices are mostly taken from the International House Price database of FED Dallas, which is borrowed from Mack and Martinez-Garcia (2011). For Austria, Greece and Portugal, I have taken the quarterly series of house prices from the Property Price Statistics of the Bank for International Settlements (BIS). For Austria, I consider the series of "Residential Property Prices, All Flats (Vienna), per square meter", for Greece I consider the series of "Residential Property Prices, All Flats (Other Cities), per dwelling", and for Portugal I consider the series. The real annual prices are taken by deflating with the according CPI series the nominal series, which has been aggregated at the annual level by taking the average over the four quarterly observations per year. For Portugal, I take the monthly series from the Property Price Statistics of the BIS, considering the series of "Residential Property Prices, All Dwellings, per square meter". The annual series is computed by taking the average over the twelve observations per year.

Table A.1: The Dates of Financial Crises and Recessions

| | Financial Crises | Recessions |
|---|---|---|
| Australia | 1989 | 1982, 1986, 1994, 2000, 2002, 2006, 2008, 2012 |
| Austria | 2008 | 1980, 1984, 1986, 1992, 1995, 2001, 2011 |
| Belgium | 2008 | 1980, 1984, 1991, 1995, 1998, 2001, 2011 |
| Canada | 2008 | 1980, 1986, 1989, 1995, 2001, 2003, 2012 |
| Denmark | 1987, 2008 | 1980, 1989, 1993, 1995, 1997, 2001, 2011 |
| Finland | 1991 | 1980, 1982, 1990, 1992, 1995, 2001, 2012 |
| France | 2008 | 1981, 1983, 1995, 1998, 2001, 2012 |
| Germany | 2008 | 1980, 1986, 1991, 1995, 2001, 2011 |
| Greece | 1991, 2009 | 1997, 2000, 2004 |
| Ireland | 2008 | 1982, 1985, 1991, 1997, 2001 |
| Italy | 1990, 2008, 2011 | 1980, 1986, 1996, 2001 |
| Japan | 1992 | 1982, 1986, 1997, 2001, 2004, 2008, 2012 |
| Netherlands | 2008 | 1980, 1986, 1991, 1995, 2000, 2011 |
| Norway | 1988 | 1980, 1991, 1996, 2001, 2008, 2012 |
| Portugal | 2008, 2011 | 1980, 1983, 1991, 1995, 2001 |
| Spain | 2008, 2011 | 1980, 1984, 1991, 1995, 2000 |
| Sweden | 1991, 2008 | 1980, 1984, 1996, 2000, 2011 |
| Switzerland | 2008 | 1982, 1986, 1994, 2000, 2002, 2006, 2008, 2012 |
| United Kingdom | 1984, 1991, 2007 | 1994, 1997, 2000, 2003, 2011 |
| United States | 2007 | 1980, 1981, 990, 2000 |

Note: The dates of financial crises come from Bordo et *al.* (2001), Caprio and Klingebiel (2003), Reinhart and Rogoff (2009), Laeven and Valencia (2012), Schularick and Taylor (2012), Jorda et *al.* (2013b). Financial crises are defined as credit crunches in which the financial sector experiences large losses and bank runs, that eventually lead to a spike in bankruptcies, forced merged and government intervention. The dates of recessions come from OECD recession indicators.

## A.2 SVAR: Volatility Shocks and the Housing Market

The VAR is estimated using with monthly data from January 1963 until December 2013 on the level of S&P 500 returns, an indicator of volatility, the Federal Funds Rate, the consumer price index, industrial production and three variables on the housing markets related to price, quantity and liquidity. Each series but the volatility indicator is taken in logarithm and detrended with a band-pass filter that removed frequencies below 18 months and above 96 months. The VAR includes a set of 12 lags.

**S&P 500 returns:** I take the logarithmic returns of the series of S&P 500 Stock Price Index provided by S&P Dow Jones Indices LLC.

**Indicator of Volatility:** The indicator of volatility is borrowed by Bloom (2009). The measure of volatility is an indicator function which equals one in the events in which the VIX index (or the volatility of daily returns within a month in case the VIX data is not available) is at least 1.65 standard deviations above its long run trend, as proxied by the HP-filtered trend.

**Federal Funds Rate:** The series is the Effective Federal Funds Rate provided by the Board of Governors of the Federal Reserve System. The FED-FRED indicator code is *FEDFUNDS*.

**Consumer Price Index:** The series is the Consumer Price Index for All Urban Consumers: All Items provided by the Bureau of Labor Statistics. The FED-FRED indicator code is *CPIAUCSL*.

**Industrial Production:** The series is the Industrial Production Index provided by the Board of Governors of the Federal Reserve System. The FED-FRED indicator code is *INDPRO*.

**House Price:** The series is the Median and Average Sales Prices of New Homes Sold provided by the Census Bureau. The series refers to new, single-family houses only. The FED-FRED indicator code is *MSPNHSUS*. In the robustness checks, I also use the series of the Conventional Mortgage Home Price Index provided by Freddie Mac, which starts in January 1975.

**Quantity of Houses Sold:** The series is the Number of Houses Sold provided by the Census Bureau. The series refers to new, single-family houses only. The FED-FRED indicator code is *HSN1F*.

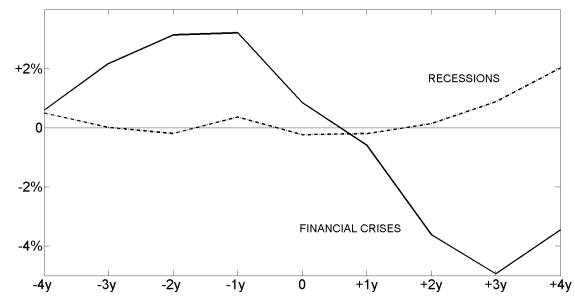
**Liquidity of the Housing Market:** The series is the Monthly Supply of Home provided by the Census Bureau. The series refers to new, single-family houses only. The series indicates the expected time of the market of houses put up on sale. The FED-FRED indicator code is *MSACSR*.

# B Dynamics around Crises and Recessions

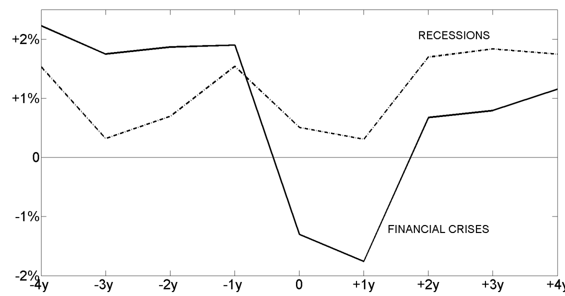
Figure B.1 plots the dynamics around financial crises and recessions of credit growth, GDP growth, the house price growth and the level of the Solow residual. Panel (a) of Figure B.1 shows that credit growth is much more volatility around financial crises than around recessions. Moreover, financial crises are preceded by a credit boom in which credit grows around 2% above trend. The trend is reversed upon the burst of the crisis, after which credit growth becomes highly negative. Instead, the dynamics around recessions do not present sizeable deviations from the long-run mean of credit growth. An analogous dynamics characterize also the GDP, the house price growth and the level of the Solow residual, as depicted in Panel (b), (c) and (d). This evidence supports the view of Reinhart and Rogoff (2009), Mendoza and Terrones (2012), Schularick and Taylor (2012), and Jorda et *al.* (2013a,b) that financial crises are booms gone bust.

Figure B.1: Dynamics around Crises and Recessions.

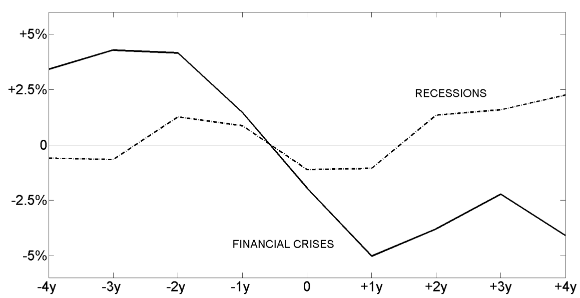
(a) Real Credit Growth



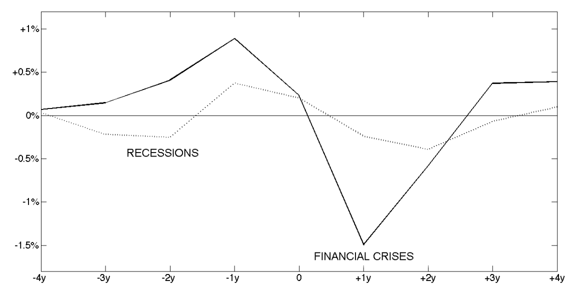

(b) Real GDP Growth




(c) Real House Price Growth




(d) Solow Residual



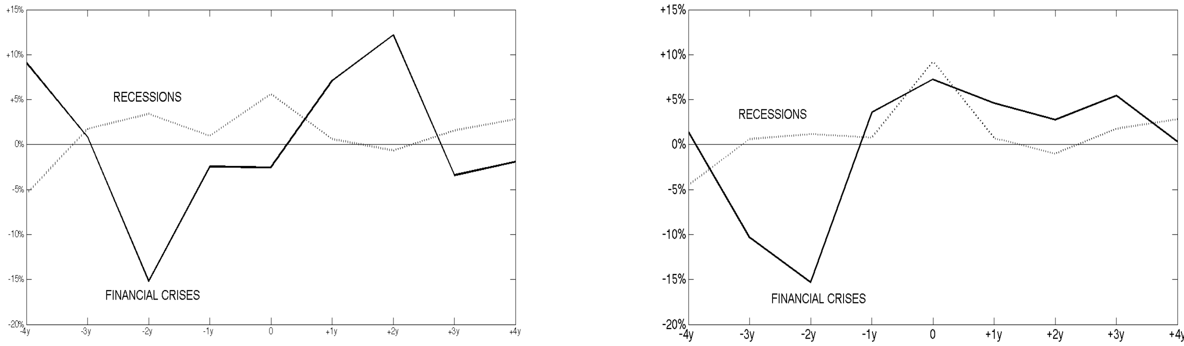

Note: The figure plots the median values of cross-country annual growth rates of real credit to the private non-financial sector (Panel a), real GDP growth rates (Panel b), real house price growth (Panel c) and the level of the Solow residual (Panel d) measured in log differences from the long-run mean - around recessions and financial crises (9 year window). The continuous line indicates the dynamics around financial crises, while the dashed line refers to recessions. The dates of financial crises are taken from Reinhart and Rogoff (2009). Recessions are derived from the OECD recession indicators.

Figure B.2 shows that the dynamics of volatility around financial crises and recessions are not altered when either computing volatility as the median values of the deviations of the Solow residual from the trend (instead of the mean as in Figure 1), or when excluding the recent financial crises episodes. Figure B.3 shows that the VIX was well below average over the three years preceding the financial crisis, and experience a surge raise at the beginning of 2007, well before the burst of the Great Recession. Over the three quarters preceding the financial crisis, the VIX has experienced a cumulative increase of around 50% from its beginning of 2007 level. This evidence suggests that a sudden volatility spike after a prolonged period of low volatility tends to lead to a financial crisis.

Figure B.2: Different Measures of Aggregate Volatility.

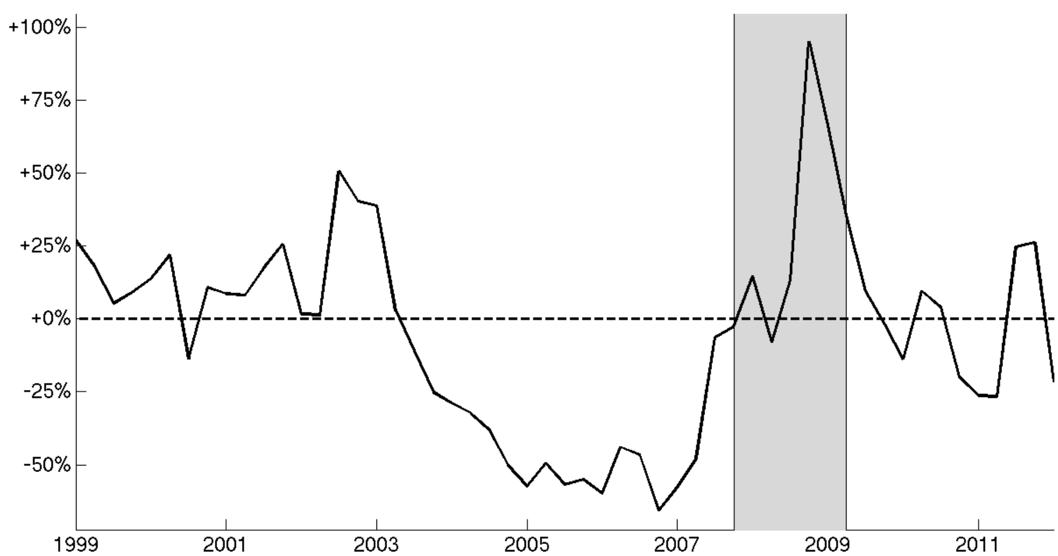
(a) Volatility of Solow Residual - Median

(b) Volatility of Solow Residual - 1980 - 2006




Note: The figure plots the dynamics of aggregate volatility around financial crises and recessions (9 year window). The continuous line indicates the dynamics around financial crises, while the dashed line presents the dynamics around recession. In Panel (a) aggregate volatility is measured as the median values of the deviations from the trend of the stochastic volatility of countries' total factor productivity. In Panel (b) aggregate volatility is measured as the median values of the deviations from the trend of the stochastic volatility of countries' total factor productivity over the period 1980-2006, therefore excluding the recent financial crisis. The dates of financial crises are taken from Reinhart and Rogoff (2009). Normal recessions are derived from the OECD recession indicators.

Figure B.3: The VIX and the Great Recession.



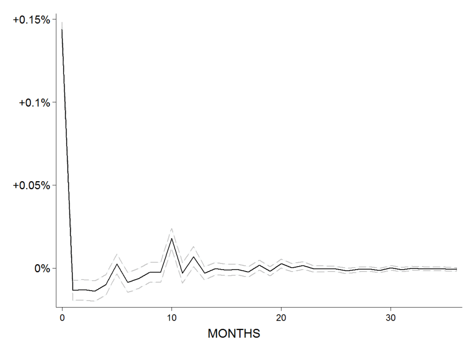

Note: The figure plots the changes in the quarterly VIX index, from January 1999 until December 2011. The series is defined as the percentage deviation from the long-run mean. The shadow area denotes the last financial crisis.

## B.1 SVAR and the House Price

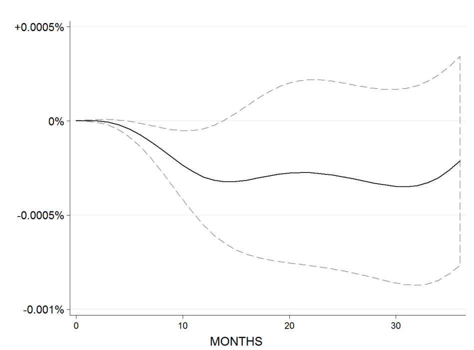
Figure B.4 shows that the impulse response functions of the housing market variables does not change even when considering a different measure of the house price, that is, the CMHPI series from Freddie Mac.

Figure B.4: Volatility Shocks and the Housing Market.

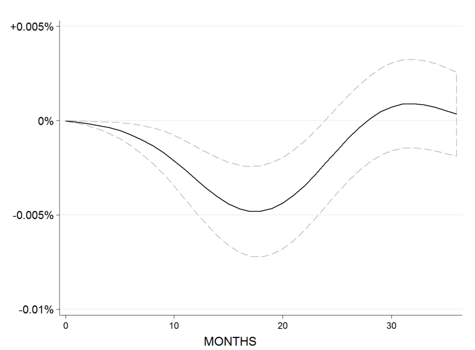
(a) Volatility



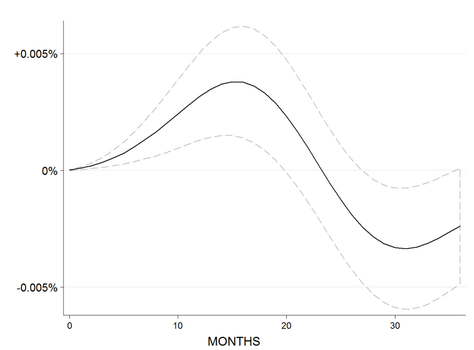

(b) House Price




(c) House Sales




(d) Time on the Market




Note: VAR estimated from January 1975 to December 2013. The dashed lines are 1 standard-error bands around the response to a volatility shock. The coordinates indicate percent deviations from the baseline.

# C Characterization of the Equilibrium

## C.1 Definition of Decentralized Equilibrium

In this environment, a recursive decentralized equilibrium is defined by the individual value function $V(h,d;H,D,z,\sigma)$ and optimal policy functions $\{\hat{c}(h,d;H,D,z,\sigma), \hat{n}(h,d;H,D,z,\sigma), \hat{s}(h,d;H,D,z,\sigma), \hat{d}'(h,d;H,D,z,\sigma)\}$, pricing functions for occupied housing $q^{\text{mkt}}(H,D,z,\sigma)$, vacant housing $q^{\text{opt}}(H,D,z,\sigma)$ and labor $w(H,D,z,\sigma)$, probabilities of selling and buying a house $P^{\text{sell}}(H,D,z,\sigma)$ and $P^{\text{buy}}(H,D,z,\sigma)$, and a perceived law of motion for aggregate bond holdings $\Gamma_D(H,D,z,\sigma)$ and occupied housing $\Gamma_H(H,D,z,\sigma)$ such that:

1. Given the pricing functions $q^{\text{mkt}}(H,D,z,\sigma)$, $q^{\text{opt}}(H,D,z,\sigma)$ and $w(H,D,z,\sigma)$, the probability of selling and buying a house, $P^{\text{sell}}(H,D,z,\sigma)$ and $P^{\text{buy}}(H,D,z,\sigma)$, and the law of motions of aggregate bond holdings $\Gamma_D(H,D,z,\sigma)$ and aggregate occupied housing $\Gamma_H(H,D,z,\sigma)$, the families' problem is solved by $V(h,d;H,D,z,\sigma)$ and $\{\hat{c}(h,d;H,D,z,\sigma), \hat{n}(h,d;H,D,z,\sigma), \hat{s}(h,d;H,D,z,\sigma), \hat{d}'(h,d;H,D,z,\sigma)\}$.

2. The housing markets clear, the probability of buying a house is

$$P^{\text{buy}}(H,D,z,\sigma) = \frac{\hat{s}(h,d;H,D,z,\sigma)\left[(1-h)\hat{s}(h,d;H,D,z,\sigma)\right]^{1-\gamma}(1-h)^{\gamma}}{(1-h)\,\hat{s}(h,d;H,D,z,\sigma)},$$

the probability of selling a home is

$$P^{\text{sell}}(H,D,z,\sigma) = \frac{\left[(1-h)\hat{s}(h,d;H,D,z,\sigma)\right]^{1-\gamma}(1-h)^{\gamma}}{1-h},$$

where the prices of occupied and vacant housing are determined by Equation (24) and (8), respectively.

3. The labor market clears at the equilibrium wage $w(H,D,z,\sigma)$.

5. The perceived law of motion of aggregate bond holdings coincide with the actual one, that is, $\Gamma_D(H,D,z,\sigma) = \hat{d}'(h,d;H,D,z,\sigma)$.

6. The perceived law of motion of the aggregate stock of occupied houses coincide with the actual

one: $\Gamma_H(H,D,z,\sigma) = (1-\psi)\big(h + P^{\text{buy}}(H,D,z,\sigma)\,\hat{s}(h,d;H,D,z,\sigma)(1-h)\big)$.

## C.2 First Order Conditions

The first order conditions of the problem yield the optimal choices on the supply of working hours, the number of workers to hire, housing investment and borrowing:

$$w_t = \frac{U_{l_t}}{U_{c_t}} \tag{C.1}$$

$$z_t F_{n_t} = w_t\left[1 + \frac{\phi_t \nu}{U_{c_t}}\right] \tag{C.2}$$

$$\begin{aligned} q_t^{\text{mkt}} + \frac{2\kappa s_t}{P_t^{\text{buy}}(1-h_t)} &= \psi \mathbb{E}_t\left[\Lambda_{t+1}\left(P_{t+1}^{\text{sell}} q_{t+1}^{\text{mkt}} + \left(1 - P_{t+1}^{\text{sell}}\right) q_{t+1}^{\text{opt}}\right)\right] + \dots \\ &\dots + (1-\psi)\,\mathbb{E}_t\left[\Lambda_{t+1}\left(V_{t+1}^H + \frac{U_{h_{t+1}}}{U_{c_{t+1}}} + e^{z_{t+1}} F_{h_{t+1}} + \frac{\phi_{t+1}}{U_{c_{t+1}}} q_{,t+1}^{\text{opt}}\right)\right] \end{aligned} \tag{C.3}$$

$$U_{c_t} = \beta R \mathbb{E}_t\left[U_{c_{t+1}}\right] + \phi_t \tag{C.4}$$

where $Y_{x_t}$ denotes the derivatives of the function $Y(\cdot)$ with respect the term $x_t$, and $\phi_t$ is the Lagrange multiplier associated to the borrowing constraint of the families.

The Equation (C.1) is the standard condition for the optimal labor supply. Instead, the optimal labor demand (C.2) is distorted by the presence of the Lagrange multiplier associated to the borrowing constraint $\phi_t$. In the states in which the borrowing constraint binds, the multiplier $\phi_t$ is positive, and the shadow price of the borrowing constraint defines a wedge above the marginal cost. Hence, when a family is borrowing constrained, the cost of hiring labor force de-facto increases, forcing the families to reduce the number of workers hired and the overall level of production.

The Equation (C.3) represents the equilibrium conditions for the search effort on the frictional market. It stipulates that in equilibrium the overall cost of searching for a house equal its marginal gain. The cost is the sum of the searching cost and the house price. The gain is the sum of the production dividends, the utility services received from occupying the house, the extra amounts of resources obtained by relaxing the borrowing constraint with an additional unit of collateral and the continuation value of owning a house. This term also considers the event in which the member is hit by a mismatch shock and forced to sell the house.

Finally, the Equation (C.4) characterizes the optimal choices of bonds. Again, the borrowing constraint adds an extra-financing cost $\phi_t$ which increases the actual repayment cost. Therefore, in the states in which the borrowing constraint binds, households de-facto incur in an interest rate that is above the one charged by foreign investors.

# D Proofs

## D.1 Equilibrium Borrowing Constraint

The derivation of the equilibrium borrowing constraint closely follows Bianchi and Mendoza (2013). The borrowing constraint arises in equilibrium as an incentive compatibility constraint which grounds on a limited enforceability of debt, that is, families lack of commitment to repay their debt. I consider the incentive compatibility constraint which yields zero expected profits for the lenders in case they seize families' collateral, and ensures that families do not default. I consider the following environment:

1. Loans are signed with lenders in a competitive environment;
2. Financial contracts are not exclusive;
3. There is no informational friction between lenders and families;
4. Families borrow during the second stage of each period of the model, that is, just after the realization of the shocks, and before production takes place;
5. Families lack of commitment in repaying the debt only during the first stage of the problem;
6. If families renege on their debt, the stock of occupied housing $h_{i,t}$ is seized by the lenders during the third stage, that is, defaulting families can still use their stock of occupied housing for production and enjoy its utility services;
7. Lenders immediately sell the liquidated housing to a real estate sector in the third stage;
8. The real estate sector consists of a continuum of real estate agencies;

9. Each family owns a diversified stake in the real estate sector;
10. There is free entry in the real estate sector, which is further perfectly competitive;
11. The real estate sector buys the liquidated houses from the lenders and puts them up on sale on the frictional market;
12. The real estate sector do not use the stock of liquidated houses either as a production input or as a collateral asset, and does not enjoy any utility service of housing;
13. After reneging on debt, families can immediately access again financial market at no penalty, and can purchase again its housing stock at competitive prices.

In this environment, in case a family defaults on its current level of debt, the lenders lose an amount of resources that equals $\frac{d_{i,t+1}}{R} + \nu w_t n_{i,t}$, and gain $q_t^{\text{opt}} h_{i,t}$ from selling the liquidated housing to the real estate sector. Hence, in equilibrium lenders will not require a collateral value larger than $q_t^{\text{opt}} h_{i,t}$.

On the other hand, from a family perspective, the gain of defaulting equals $\frac{d_{i,t+1}}{R} + \nu w_t n_{i,t}$ while its cost is $V_{i,t}^H h_{i,t}$, that is, the value that families attribute to the stock of housing seized by the lenders. Since $V_{i,t}^H h_{i,t} \geq q_t^{\text{opt}} h_{i,t}$, families will always decide to repay back their debt. Thus, the borrowing constraint

$$\frac{d_{i,t+1}}{R} + \nu w_t n_{i,t} \leq q_t^{\text{opt}} h_{i,t}$$

ensures that lenders do not make ex-ante profits on a defaulting family and that families do not default in equilibrium. In this way, the real estate sector does not operate on an equilibrium path.

## D.2 Proof of Proposition 1.

The loan-to-value ratio $\frac{q_t^{\text{opt}}}{q_{h,t}}$ equals

$$\frac{q_t^{\text{opt}}}{q_t^{\text{mkt}}} = P_t^{\text{sell}} + \left(1 - P_t^{\text{sell}}\right) \mathbb{E}_t \left[\Lambda_{t+1} q_{t+1}^{\text{opt}}\right]$$

In a steady-state equilibrium, the loan-to-value ratio equals

$$\frac{q^{\text{opt}}}{q^{\text{mkt}}} = P^{\text{sell}} + \left(1 - P^{\text{sell}}\right) \beta \frac{q^{\text{opt}}}{q_{\text{mkt}}} = \frac{P^{\text{sell}}}{1 - \left(1 - P^{\text{sell}}\right) \beta}$$

since $\Lambda_{t+1} = \beta \frac{U_{c_{t+1}}}{U_{c_t}}$, and $U_{c_{t+1}} = U_{c_t} = U_c$ along the steady-state. Thus, the derivative of the loan-to-value ratio with respect to a change in the current level of the liquidity of the frictional housing market, measured in terms of probability of selling a house is

$$\frac{\partial \frac{q^{\text{opt}}}{q^{\text{mkt}}}}{\partial P^{\text{sell}}} = \frac{1-\beta}{\left[1-\left(1-P^{\text{sell}}\right)\beta\right]^2} > 0 \qquad \forall \beta \in (0,1),\ P^{\text{sell}} \in (0,1)$$

## D.3 Proof of Proposition 2.

I use the equation of house price $q_{w,t}$ given by the condition (24) to characterize the expected equity premium associated to the investment in housing

$$\mathbb{E}_t\left[R^{ep}_{t+1}\right] = \mathbb{E}_t\left[R^h_{t+1} - R\right]$$

where $R^h_{t+1} = \frac{e^{z_{t+1}} F_{h_{t+1}} + q^{\text{mkt}}_{t+1}}{q^{\text{mkt}}_t}$ denotes the cum-dividend return on housing investment. The equity premium reads

$$\begin{aligned}
\mathbb{E}_t\left[R^{ep}_{t+1}\right] = \frac{1}{\mathbb{E}_t\left[\Lambda_{t+1}\right]}\Bigg\{ & \underbrace{\frac{\phi_t}{U_{c_t}}}_{\text{Collateral}} + \underbrace{\mathbb{E}_t\left[\Lambda_{t+1}\Delta q^{\text{mkt}}_{t+1}\left(1-\frac{q^{\text{opt}}_{t+1}}{q^{\text{mkt}}_{t+1}}\right)\right]}_{\text{Search Frictions}} + \underbrace{\mathbb{E}_t\left[\Lambda_{t+1}\Omega_{t+1}\right]}_{\text{Mismatch \& Bargaining}} \\
& - \underbrace{\mathbb{E}_t\left[\Lambda_{t+1}\Delta q^{\text{mkt}}_{t+1}\frac{V^H_{t+1}}{q^{\text{mkt}}_{t+1}}\right]}_{\text{Continuation Value Match}} - \underbrace{\mathbb{E}_t\left[\Lambda_{t+1}\Delta q^{\text{mkt}}_{t+1}\frac{\phi_{t+1}}{U_{c_{t+1}}}\frac{q^{\text{opt}}_{t+1}}{q^{\text{mkt}}_{t+1}}\right]}_{\text{Collateral} \times \text{Search Frictions}} - \underbrace{\mathbb{C}_t\left[R^{ep}_{t+1}, \Lambda_{t+1}\right]}_{\text{Risk}}\Bigg\}
\end{aligned}$$

where

$$\begin{aligned}
\Omega_{t+1} = {} & \zeta\psi\mathbb{E}_t\left[\Lambda_{t+1}\Delta q^{\text{mkt}}_{t+1}\left(1-P^{\text{sell}}_{t+1}\right)\left(1-\frac{q^{\text{opt}}_{t+1}}{q^{\text{mkt}}_{t+1}}\right)\right] + \zeta\mathbb{E}_t\left[\Lambda_{t+1}\Delta q^{\text{mkt}}_{t+1}\left(1-\frac{q^{\text{opt}}_{t+1}}{q^{\text{mkt}}_{t+1}}\right)\right] + \\
& + \left(1-(1-\psi)\zeta\right)\mathbb{E}_t\left[\Lambda_{t+1}\Delta q^{\text{mkt}}_{t+1}\frac{V^H_{t+1}}{q^{\text{mkt}}_{t+1}}\right] + \left(1-(1-\psi)\zeta\right)\mathbb{E}_t\left[\Lambda_{t+1}\Delta q^{\text{mkt}}_{t+1}\frac{\phi_{t+1}}{U_{c_{t+1}}}\frac{q^{\text{opt}}_{t+1}}{q^{\text{mkt}}_{t+1}}\right] + \\
& + \left(1-(1-\psi)\zeta\right)\mathbb{E}_t\left[\Lambda_{t+1}\Delta q^{\text{mkt}}_{t+1}\frac{z_{t+1}F_{h_{t+1}}}{q^{\text{mkt}}_{t+1}}\right] - \zeta\psi\mathbb{E}_t\left[\Lambda_{t+1}\Delta q^{\text{mkt}}_{t+1}\right]
\end{aligned}$$

The formula above highlights that the premium, and therefore the house price, depends on collateral values and search frictions. Indeed, in standard asset pricing conditions, the equity return depends only the level of risk, that is, the covariance between families' stochastic discount factor and the equity premium. Here, the equity premium is also increasing in the current Lagrange multiplier associated to the borrowing constraint $\phi_t$ and the search frictions as measured by the margin of the borrowing constraint. On one hand, when the borrowing constraint binds, the equity premium rises, and the house price $q_t^{\text{mkt}}$ declines. Thus, borrowing constrained families that are forced to fire sales depress the current house price. On the other hand, when the future probability of selling houses in the frictional market decreases, tightening the borrowing margin, the equity premium rises and therefore the house price declines. So, a liquidity freeze lowers the house price. In either case, there is also an indirect effect. The high equity return in the states in which the borrowing constraint binds and the liquidity of the housing market is low tends to be associated by disproportionately higher levels of families' marginal utility of consumption. This comovement further depresses the house price.