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DEMS WORKING PAPER SERIES

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No. 513 – February 2023

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http://dems.unimib.it/

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February 15, 2023

Abstract

The aim of this paper is to empirically identify the state of the US housing market and to set state-dependent policy rules to smooth the housing cycle. I do so by estimating a three states Markov-switching model of housing prices in which mortgage debt is the state-dependent variable. As a result, the housing market state might be classified as being in housing booms fueled by credit, normal or implosion times. Second, I propose a state-contingent policy rule fed with the probabilities of being in each state. I apply such rule to set a housing countercyclical capital buffer (SCCyB) and a time-varying home mortgage interest deduction rule. Finally, I show that such rules have forecasting ability to predict the charge-off rates on real estate residential loans. The significance of this study is that it informs policymakers about the state of the housing market mechanically while it also provides a simple rule that allows the implementation of state-contingent macroprudential policy. Further, the structure of such rule is general enough to be applied to other policy tools.

Keywords: Housing prices, non-linear modeling, Markov switching model, housing demand, household debt, macroprudential policy.

JEL Classification: C22, C24, G51, R21, R31.

*This paper is an improved version of the first chapter of my PhD in Economics at the *University of Milano-Bicocca* which was previously circulated as "Housing booms fueled by credit". I would like to thank Matteo Pelagatti and Vittoria Cerasi for their advice and Andrea Bastianin for his constructive comments. An anonymous referee, John V. Duca, Dirk Bezemer and other seminar participants at the "Minsky at 100" conference at the *Università Cattolica del Sacro Cuore* (Milan, 2019), at the 28th Annual Symposium of the *Society for Nonlinear Dynamics and Econometrics* (virtual, 2020), at the RCEA-Europe Conference on Global Threats to the World Economy (virtual, 2023) and at internal seminars at Banco de Portugal and the National Bank of Slovakia provided me interesting discussions and suggestions.

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1 Introduction

The Global Financial Crisis and the related literature on the effects of housing and credit booms in the economy raised a consensus about the danger that such phenomena pose to financial stability. Indeed, a large body of evidence identifies excessive credit growth as a good predictor of financial crises (Cerutti et al., 2017b, among others). A direct consequence of this realized turmoil was the introduction of new banking regulation to avoid excessive build-up of credit risk. However, how to set macroprudential policy, for instance the counter-cyclical capital buffer (CCyB) and the sectoral CCyB (SCCyB), is still an open issue. In particular, current methods for estimating housing prices overvaluation and excessive credit do not seem fit for the job. First, what is systemically dangerous about housing bubbles is being financed with debt, not the prices by itself (Crowe et al., 2013; Jordà et al., 2015). Second, the credit-to-GDP gap as a CCyB driver present several challenges (Babic and Fahr, 2019). Such threats might provide weak comfort to policymakers in implementing timely counter-cyclical policies, in turn giving room to *inaction bias*. Additionally, electoral cycles might further dampen the incentives of fiscal policymakers to deal with this issue actively (Müller, 2022).

In the last decade, theoretical studies incorporating rational bubbles in macro models used a device called *market psychology*, i.e. a regime-switching random process such that the economy can be in a fundamental or in a bubbly state (Martín and Ventura, 2011 and subsequent papers). This agnostic mechanism and financial frictions are two key ingredients around which they construct a framework for analyzing the interaction between rational bubbles and credit where the former provide collateral. The policy prediction in this type of model is that a policymaker can implement the desired Pareto-optimal bubble allocation by setting the appropriate counter-cyclical credit management policy. However, before making any action an interested policymaker must identify which is the current market psychology that will feed its policy rule.

This paper addresses the question by estimating a three states Markov switching model in which house price growth is explained by standard housing demand fundamentals plus mortgage debt growth, which is the state-dependent variable that also drives the transition probabilities between each state (consistent with Stein, 2021). In doing so, I depart from the empirical literature on bubble testing and focus instead on identifying periods of *housing booms fueled by credit*, i.e. states in which there is high growth in house prices and mortgage debt, once controlling for standard housing demand fundamentals. In this way, I narrow down the search of this systemic risk source, along the lines of Crowe et al., (2013). Additionally, I argue that the other two states are normal times and busts, an interpretation that is consistent with what theory predicts in each state. In proceeding this way, I provide the distinction between housing market states that might allow a counter-cyclical and state-dependent credit management policy as proposed theoretically by Martín and Ventura (2011) and empirically by Drehmann et al. (2010).

The described approach overcomes some key challenges that alternative methods face. Regarding the literature on testing for house price bubbles, the threats are essentially three. First, this literature most often, if not always, is trying to find bubbles or explosive behavior in house prices, which for macroprudential purposes, is not that relevant because, as highlighted above, what makes a bubble dangerous is being financed with debt, not the asset overvaluation itself (Jordà et al., 2015). For this reason, bubble tests are not well suited for macroprudential policy discussions. Second, the models used for this purpose are actually very stylized, leaving room for relevant variables omissions. Third, in practice, similar econometric models used for identifying overvaluation often provide inconsistent results (ESRB, 2022), so using them for policy purposes might seem excessive. With regard to using the credit-to-GDP gap to guide the CCyB, some potential drawbacks are the following. First, credit is a broad concept that may include also non-risky chunks. Second, it employs GDP as a normalization, which is subject to delays and large revisions. Third, it uses the Hodrick-Prescott filter as a detrending procedure for credit.

The contributions of this study are the following. First, I provide an empirical tool to identify the states of the housing *market psychology* along the lines of Martín and Ventura (2011). Secondly, in doing so I focus the attention on identifying *housing booms fueled by credit*, instead of asset price bubbles, therefore providing a stronger narrative for triggering macroprudential action as this approach considers also mortgage debt. Third, I use the Markov-switching results to deploy a simple rule for setting a sectoral counter-cyclical capital buffer (SCCyB) and a home mortgage interest deduction rule. Finally, I show that adding such tools improves the forecasting accuracy of a benchmark FAVAR model in predicting charge-off rates on real estate residential loans, which might give support to using the described methods to deal with housing booms fueled by credit. Interestingly, such policy rule structure is general enough to be applied to other policy tools.

Related literature. This paper relates to several strands of literature. First, the focus of this study is motivated by empirical works analyzing the effects of housing booms accompanied by credit booms on the economy and on financial stability (Mian and Sufi, 2009, 2010, 2011, 2014, 2018, 2022, Jordà et al., 2012, 2015a, 2015b, 2016, 2017, Cerutti et al. 2017b, Schularick and Taylor, 2012, among many others). These studies document that credit booms tend to boost housing prices and in turn the risk of financial crises. This evidence is the main motivation in this paper and therefore it is crucial in inspiring the modeling choices made, notably behind the regime-switching model of *housing booms fueled by credit*.

Second, this paper is also related to theoretical studies modeling rational bubbles in macro models. Despite the fact that *speculative manias* have been around for centuries (Kindleberger, 1978), the introduction of bubbles in macro models is relatively recent. The seminal contributions in this arena correspond to Samuelson (1958) and Tirole (1985), the first in dealing with the challenges of this agenda, such as dynamic inefficiency and the difficulties of these models to generate expansionary effects during booms. In this paper I follow the approach of Martín and Ventura (2011) and their subsequent contributions in considering the housing *market psychology* as a plausible device to identify periods of housing booms fueled by credit, normal times and busts. Their market psychology follows a two states Markov process such that the economy can be either in a bubbly or in a fundamental state, where the transition probabilities between states are random. Instead, I relax this assumption by allowing transition probabilities to depend on mortgage debt growth in a three states Markov switching model. A more detailed summary of this literature is provided in the next section.

Third, this analysis is also complementary to the empirical studies measuring or dating periods of house prices overvaluation, where there appear three different approaches. One approach consists in estimating a "fundamental" house price using an econometric model, and deriving the deviations from actual prices, an approach that is extensively used in central banks (ESRB, 2022). A second avenue is testing for mildly explosive behavior as proposed by Phillips et al. (2011, 2015), which exploit augmented Dickey-Fuller tests to find *exuberance* in asset prices. This method is used by the Federal Reserve Bank of Dallas to periodically report housing exuberance results in the US and other countries (Pavlidis et al., 2016). A third and relatively underused approach is to employ regime-switching models to date periods that are characterized by high or low prices (Van Norden and Schaller, 1993, 1996). Despite all these efforts, the task of identifying bubbles still faces well known challenges, namely the omission of relevant fundamental variables and the distinction between bubbles or time-varying fundamentals (see Gürkaynak, 2008 and Homm and Breitung, 2012). In this paper, instead of trying to identify housing bubbles I define a Markov-switching model designed to identify housing booms fueled by credit in the booming state, which is done by introducing mortgage debt as a state-dependent variable in the house price equation, while also controlling for standard housing demand fundamentals. I argue that this identification strategy is better suited for the states to be exploited as macroprudential policy drivers given that the housing booms fueled by credit combine both high house prices and debt growth.

Finally, this paper also relates to the literature on macroprudential policy in scenarios of housing and credit booms. While during the 2000s there was no consensus regarding the appropriate policy response to housing price bubbles (Bernanke, 2002; Roubini, 2006), the acute turmoil amid the Global Financial Crisis made clear that better banking regulation would help in mitigating systemic risks, namely via the so-called borrower-based measures (Aikman, 2021) and capital buffers (BIS, 2011, 2019a, 2019b). Despite being available to banking regulators for almost a decade, how to calibrate them remains a challenge. Regarding the counter-cyclical capital buffer CCyB, while the credit-to-GDP gap is its suggested driver (BIS, 2010), it is subject to empirical challenges and there is no general agreement on how to set it. These might help explain the lack of time-variation in this policy tool in the US (Stein, 2021) and why it is not generally followed by central banks (Döme and Sigmung, 2023). In this paper I show that a Markov switching model of housing booms fueled by credit can be used to feed a policy rule to set both a housing CCyB (SCCyB) and a home mortgage interest deduction rule.

The structure of this paper is as follows. Section 2 presents the theoretical framework and describes the data and the macroeconometric approach, notably the Markov-switching model of housing booms fueled by credit. Section 3 showcases the empirical results of such model. Section 4 proposes a simple policy rule for setting a housing SCCyB and a home mortgage interest deduction rule by exploiting the identified housing states of the Markov-Switching model. Section 5 discusses the potential caveats of this work. Finally, section 6 concludes.

2 Model specification

2.1 Theories of rational bubbles

The literature studying macro models with rational bubbles dates back to Samuelson (1958) and Tirole (1985), which provided the seminal contributions in this agenda[1]. This *traditional view* on housing bubbles dealt with two key challenges. First, their equilibrium could be dynamically inefficient, which appears to happen whenever the steady state interest rate is below the growth rate of the economy. Indeed, this issue comes from the classical assumption that the interest rate in the economy equals the marginal return to investment. Second, they focus on deterministic bubbles which are predictable and do not burst, which turns out to be at odds with reality. This opened the door to consider instead stochastic bubbles along the lines of Blanchard (1979), where bubbles are consistent with rational expectations. However, in the later bubbles can only arise under low interest rates, which in practice is equivalent to dynamic inefficiency.

To overcome the dynamic inefficiency issue, modelers introduced frictions which allow the interest rates to be low enough to generate bubbles in dynamically efficient economies. One approach along these lines is to introduce externalities in capital accumulation in economies with endogenous growth (Saint-Paul, 1992). An alternative avenue is to consider borrowing constraints which manage to depress interest rates enough to create bubbles (Woodford, 1990). Despite these successes, these models predict that bubbles crowd-out capital and reduce output, which turns out to be at odds with the economic developments observed in the latest two decades both in the US and Europe. Olivier (2000) amends this shortcoming by considering bubbles on different assets. Then, while equity bubbles can boost investment and economic growth, bubbles on unproductive assets crowd-out productive investment and curtail growth. An alternative path to address such issue is to consider the *financial accelerator* mechanism (Bernanke and Gertler, 1989, Kiyotaki and Moore, 1997), which also allow bubbles to be expansionary while relaxing the conditions for the existence of bubbles as well.

The modeling approach on rational bubbles that I follow in this paper builds on Martín and Ventura (2011, 2012) and their subsequent contributions with additional coauthors. Indeed, using a financial accelerator mechanism, they propose a framework in which fluctuations in collateral are an important driver of credit booms and busts. In this environment, they make a distinction between states in the economy characterized by a *fundamental* collateral backed by expectations of future profits, and states in which the collateral is instead *bubbly*, so that it is backed by expectations of future credit. For getting more into details in the rest of this subsection, I pick Martín and Ventura (2018) as a reference because of its simplicity and generality and summarize the key elements of their theory that I use to motivate the empirical regime-switching setup I adopt in this paper. These authors propose a small open economy populated by two overlapping generations that live for two periods. Domestic residents and foreigners interact in the credit market, where they trade consumption goods today for consumption goods promises in the future. While some features of their model are standard, such as their production of consumption goods and their markets for factors labor and capital, the action starts on the young firm owners borrowing limit, defined as:

$$R \cdot f_t \leq \gamma \cdot E_t v_{t+1} \tag{1}$$

[1] For a survey of this literature see Martín and Ventura (2018).

meaning that the return of borrowing or credit f_t given a world interest rate R can't be higher than a share γ of the expected market value of all firms after the rental has been distributed to firm owners v_t in the next period[2]. This is an already classical borrowing constraint linking credit f_t to asset values v_t. The action comes from the latter.

Indeed, the asset value of the existing firms are given by:

$$v_t = (1-\delta)\cdot k_t + b_t \tag{2}$$

where b_t is the bubble component of firm values, which is then the reason why the market value of all firms v_t might be different than the after depreciation δ capital k_t.

Actually, the bubble has two sources such that it combines the bubbles attached to old firms b_t and the creation of new bubbles attached to new firms n_t, which is formalized as follows:

$$\gamma\cdot b_{t+1} = g_{t+1}\cdot(b_t+n_t) \tag{3}$$

which assumes that a share γ of old bubbles in next period b_{t+1} is equal to the growth rate of bubbles in the next period g_{t+1} multiplied by both bubbles old b_t and new n_t in the current period.

The key additional feature in Martín and Ventura (2018) is the so-called *market psychology*. This is a set of assumptions that define the bubble and its evolution, which are consistent with maximization and market clearing. Instead of using a market psychology that rules out bubbles leading to standard economic dynamics, they consider one in which the economy transits between two states, such that $\eta_t \in B, F$. During a bubbly state B, new bubbles pop up, while during the fundamental state, no bubbles arise. Given transition probabilities from the bubbly to the fundamental state and vice-versa, the new bubble n_t can be 0 or a positive η such that:

$$n_t = \begin{cases} \eta & \text{if } z_t = B \\ 0 & \text{if } z_t = F \end{cases} \tag{4}$$

where the transition between these two states is assumed to be random and unrelated to economic conditions[3]. This is a stylized version of a market psychology. Additionally, these authors also consider more complex environments in which in the transition between the bubbly and the fundamental state, a fraction of the old bubbles burst and is lost, which in practice we might interpret as a three states regime-switching mechanism such that the economy can be in the fundamental state, in the bubbly state and it can also burst. In any case, the interpretation is that in some periods, investor sentiment convinces markets to invest in new bubbles, while in some other periods this does not happen.

In this economy, the maximization problem of the young reads as follows:

$$\begin{aligned} \max \gamma\cdot E_t c_{t+1} \quad &= (r_{t+1}+1-\delta)\cdot\gamma\cdot k_{t+1} + E_t g_{t+1}\cdot(x_t\cdot b_t+n_t) - R\cdot f_t \\ \text{s.t.} \quad & \gamma\cdot k_{t+1} + x_t\cdot b_t = w_t + f_t \\ & R\cdot f_t \leq (1-\delta)\cdot\gamma\cdot k_{t+1} + E_t g_{t+1}\cdot(x_t\cdot b_t+n_t) \end{aligned} \tag{5}$$

where x_t is the bubble demand by the young as a share of the aggregate bubble, and the choice variables are borrowing f_t, capital stock k_{t+1} and the bubble demand x_t. Notably, the new bubbles

[2]All quantity variables are expressed in efficiency units, denoted in lower case letters.

[3]Other papers in this stream of literature including a market psychology along these lines are Martín and Ventura (2011, 2012, 2016) and Asriyan et al. (2021).

n_t is not a choice variable because it is exogenous, as it is part of the market psychology. Additionally, individual maximization and market clearing implies that $E_t g_{t+1} = R$, meaning that the expected bubble growth equals the world interest rate.

According to this theory of rational bubbles, the market psychology affects capital accumulation and growth, which can be seen in the law of motion of the capital stock, which is such that:

$$\gamma \cdot k_{t+1} = \min\left\{ \frac{R}{R+\delta-1} \cdot \left[(1-\alpha) \cdot A \cdot k_t^{\alpha} + n_t\right], \gamma \cdot \left(\frac{\alpha \cdot A}{R+\delta-1}\right)^{\frac{1}{1-\delta}} \right\} \tag{6}$$

which depends on the size of new bubbles n_t, but not on the size of old bubbles. In words, in the bubbly state, n_t is positive and the law of motion for capital is shifted up, such that if the borrowing limit is binding, bubbly periods boost capital accumulation, wealth and economic growth. In particular, each extra unit of wealth can be used to invest $\frac{R}{R+\delta-1}$ units of capital, which corresponds with the *wealth effect* of new bubbles.

In this framework, given any initial condition, capital converges to the interval $[k_F, k_B]$, i.e. the steady state capital in each state, and moves within it indefinitely. In the bubbly state, the model predicts that asset values, foreign borrowing and investment are high and the economy grows, as also consumption and welfare. Instead, in the fundamental state, asset values, foreign borrowing and investment are low, the economy weaken and consumption and welfare decrease.

Despite the apparent realism of these predictions, this theoretical framework faces three key challenges if the goal of an interested economist is to exploit it in reality. First, a macro-prudential regulator should have to learn which is the state of the market psychology before thinking about which policy to implement, which in practice is not trivial. In the process, we certainly would expect delays in this learning. Second, the transitions between states are random, which might be a bit uncomfortable to policymakers. Third, in dealing with these challenges, one still has to choose which bubbles to target; for instance stock market, housing bubbles, both, or even others.

This paper addresses such challenges in the following ways. First, I choose to focus the attention on housing booms fueled by credit, instead of just house price bubbles, stock market bubbles or some combined measure. This is motivated by the abundant evidence pointing out that what is dangerous about bubbles is being financed with debt, which is linked to financial crisis (see Jordà et al., 2015 and Cerutti et al., 2017b, *inter alia*). Second, I estimate a housing market psychology by using a three states Markov-switching model of house prices, in which mortgage debt enters in the model as a state-dependent variable. All the details regarding this model are explained in subsection 2.3. Third, I model the state transition probabilities as being dependent on mortgage debt, so they are not just random, which seems to be not an unrealistic assumption.

Regarding the usefulness of the described framework for policy execution, Martín and Ventura (2016) evaluate potential policies that governments or central banks might implement in order to allow a desired bubble size. They find that using credit management policies, namely through countercyclical taxes and subsidies on credit, policymakers can actually implement a Pareto-optimal *leaning against the wind* policy. However, given that this policy is contingent on the market psychology present at each point in time, a pre-condition for its success is to correctly estimate which is the state of such market psychology. This is my model-based motivation for estimating the Markov-switching model explained later in this section.

2.2 Data

The sample size starts in January 1984, i.e. avoiding possible issues coming from the structural break in aggregate volatility before the *Great Moderation*, and it ends June 2019, so that it also avoids possible complications arising from the extreme volatility observed during the Covid-19 pandemic.

The house price index used in the baseline Markov-switching model is the S&P Case-Shiller home price index, where the alternatives are the house price index computed by the Federal Housing Finance Agency (FHFA, henceforth), and the 10-City and 20-City composites also offered by S&P Case-Shiller. The reasons for using the S&P Case-Shiller home price index as the baseline US housing price time series are twofold. First, because it is a nationwide measure, which fits the scope of this paper. Second, because the data source they use for computing the index relies on the records that are registered in local government deeds recording offices (see S&P Dow Jones Indices, 2019) instead of records in a particular banking institution, which would make the index a function of the decision making of such firm at different levels such as the lending standards, refinancing and securitization policies[4].

Beyond housing prices, the main time series that are also used in this paper are the fundamental drivers of housing demand or those related to housing finance. As part of the first block, I consider a measure of employment (*all employees: total non-farm payrolls*, noted by E), wages (*gross domestic income: compensation of employees, paid: wages and salaries*, noted by W) and housing rental prices (*CPI for urban consumers: rent of primary residence*, noted by R), i.e. standard measures of income and purchasing capacity commonly used in the literature. In the second group of variables I consider a measure of mortgages debt (*mortgage debt outstanding, individuals and other holders*, noted by D). Table 6 in the Appendix lists all these time series.

2.3 Markov switching model of housing booms fueled by credit

The Markov switching model of house prices adopted in this paper is an extension to Markov chains with time-varying transition probabilities, drawing from Hamilton (1986) applied in the housing sector. The motivation for using such model is twofold. First, the target in this study is to identify different states in the housing *market psychology* along the lines of Martín and Ventura (2018), which in turn define it in terms of Markov chains (see subsection 2.1). As these authors suggest, this makes sense because the volatility in such variables does not seem to be regarded to the outcome of a perfectly foreseeable event, but instead as a random variable that we might call *state*. The hope behind this approach is that by knowing the current state in the housing market, policymakers might have key information that would allow them to implement the loose, contractive or neutral policy that might be necessary to smooth the housing cycle. Second, I am particularly interested in identifying housing booms fueled by credit, as they have been extensively highlighted in the empirical literature as a key macro danger. As I show below, a Markov-switching model is flexible enough to identify housing states characterized by high house prices and debt growth, after controlling for standard housing demand determinants.

[4]The house price index computed by the Federal Housing Finance Agency relies on the records obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac (see www.fhfa.gov).

Let us define HP_t as the log-difference of the nationwide house prices index in period t, let X_t be a vector of state independent variables, let Y_t be a vector of state dependent variables and s_t be the latent state variable that defines the state of the real estate sector such that:

$$HP_t = \phi_{0,s_t} + \phi_1' X_t + \phi_{2,s_t}' Y_t + \varepsilon_t \tag{7}$$

where $\varepsilon_t \sim (0, h_{s_t})$.

For simplicity, let's assume that there are two states, denoted 1 and 2, so that s_t = 1 or s_t = 2. Therefore, depending on the state, the coefficients and variance of the state-dependent terms can be either ($\phi_{0,1}$, $\phi_{2,1}$, h_1) or ($\phi_{0,2}$, $\phi_{2,2}$, h_2).

The state transition probabilities are assumed to follow a first-order Markov chain such that:

$$p_t = P(s_t = 1 | s_{t-1} = 1, \omega_{t-1}) = p(\omega_{t-1}) \tag{8}$$

$$1 - p_t = P(s_t = 2 | s_{t-1} = 1, \omega_{t-1}) = 1 - p(\omega_{t-1}) \tag{9}$$

$$q_t = P(s_t = 2 | s_{t-1} = 2, \omega_{t-1}) = q(\omega_{t-1}) \tag{10}$$

$$1 - q_t = P(s_t = 1 | s_{t-1} = 2, \omega_{t-1}) = 1 - q(\omega_{t-1}) \tag{11}$$

where ω_{t-1} is a vector of variables that are known in period $t-1$ that affect the state transition probabilities in period t. The standard formulation of the Markov switching model assumes that these transition probabilities are constant. Instead, I will assume that they are time-varying and dependent on mortgage debt, as it is explained below.

The parameters of this model are obtained by maximum likelihood estimation. Let θ be the vector of parameters entering the likelihood function for the data and supposing that the density conditional on being in state $j, \eta(HP_t \mid s_t = j, X_t, Y_t; \theta)$ is Gaussian:

$$\eta(HP_t \mid \Omega_{t-1}, s_t = j; \theta) = \frac{1}{\sqrt{2\pi h_j}} \exp\left(\frac{-(HP_t - \beta_{0,s_t} - \beta_1' X_t - \beta_{2,s_t}' Y_t)^2}{2h_j} \right) \tag{12}$$

for j = 1,2. The information set Ω_{t-1} contains X_{t-1}, Y_{t-1}, HP_{t-1}, ω_{t-1} and lagged values of these variables, such that: $\Omega_{t-1} = \{X_{t-1}, Y_{t-1}, HP_{t-1}, \omega_{t-1}, \Omega_{t-2}\}$.

Notice that in this formulation I assume a constant relationship between the conditioning factors Y_t and house prices within each state, but allow these coefficients to vary between states. Alternatively, the relationship between the conditioning factors X_t and house prices is constant.

The log-likelihood function takes the form:

$$\ell(HP_t \mid \Omega_{t-1}; \theta) = \sum_{t=1}^{T} \ln(\phi(HP_t \mid \Omega_{t-1}; \theta)) \tag{13}$$

where the density $\phi(HP_t \mid \Omega_{t-1}; \theta)$ is obtained by summing the weighted probability state densities, across the two possible states, such that:

$$\phi(HP_t \mid \Omega_{t-1}; \theta) = \sum_{j=1}^{2} \eta(HP_t \mid \Omega_{t-1}, s_t = j; \theta) P(s_t = j \mid \Omega_{t-1}; \theta) \tag{14}$$

being $P(s_t = j \mid \Omega_{t-1}; \theta)$ the conditional probability of being in state j at time t given information set Ω_{t-1}.

The conditional state probabilities can be obtained recursively such that:

$$P(s_t = i \mid \Omega_{t-1};\theta) = \sum_{j=1}^{2} P(s_t = i \mid s_{t-1} = j, \Omega_{t-1};\theta) P(s_{t-1} = j \mid \Omega_{t-1};\theta) \tag{15}$$

Finally, by Bayes' rule the conditional state probabilities can be written as:

$$\begin{aligned} P(s_{t-1} = j \mid \Omega_{t-1};\theta) &= P(s_{t-1} = j \mid HP_{t-1}, X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2};\theta) \\ = \frac{\eta(HP_{t-1} \mid s_{t-1} = j, X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2};\theta) P(s_{t-1} = j \mid X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2};\theta)}{\sum_{j=1}^{2} \eta(HP_{t-1} \mid s_{t-1} = j, X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2};\theta) P(s_{t-1} = j \mid X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2};\theta)} \end{aligned} \tag{16}$$

In particular, two models are specified. First, let HP_t be the S&P Case-Shiller home price index in month t, let the variables wages W_t, employment E_t and rents R_t be state-independent fundamental variables of housing demand and mortgage debt D_t be the state-dependent variable which affects non-linearly housing prices[5], the three states Markov switching baseline model is such that[6]:

$$HP_t = \beta_{0,s} + \beta_1 W_t + \beta_2 E_t + \beta_3 R_t + \beta_{4,s} D_t + \varepsilon_t \tag{17}$$

where $s = [1,2,3]$ and $\varepsilon_t \sim N(0, h_{st})$. In this way is captured the idea of Geanakoplos (2009) that leverage cycles can simultaneously lead growth in debt and housing prices[7]. Implicitly, I am making two assumptions in this specification. First, the fundamental dynamics of house prices are well approximated by standard fundamentals of housing demand and *dividends* such as wages, employment and rents, which do not have a role in boom-bust state-dependencies. Second, the possible excess of demand leading to boom-bust cycles is driven by credit[8].

The conditional variance of HP_t is given by:

$$\ln(h_{st}) = \lambda_{0,s} \tag{18}$$

The state transition probabilities are specified as follows:

$$p_t = prob(s_t = 1 \mid s_{t-1} = 1, \Omega_t) = \Phi(\pi_{0,p} + \pi_{1,p} D_t) \tag{19}$$
$$q_t = prob(s_t = 2 \mid s_{t-1} = 2, \Omega_t) = \Phi(\pi_{0,q} + \pi_{1,q} D_t) \tag{20}$$
$$z_t = prob(s_t = 3 \mid s_{t-1} = 3, \Omega_t) = \Phi(\pi_{0,z} + \pi_{1,z} D_t) \tag{21}$$

[5] It is standard in the literature to employ measures of income and rental prices as fundamental variables of housing prices, and also assuming that overvaluation might be related to non-linear relationships between prices and some determinants, for instance credit (see IMF, 2019 and Gürkaynak, 2008, among others).

[6] The choice for determining the number of states in the baseline model depends on two elements. First, considering the target of this model it is assumed that the minimum number of states that should be present are three, which may potentially correspond to normal times, booms and bursts, along the lines of Martín and Ventura (2018) in their specification including a bursting loss in the transition between the fundamental and the bubbly state. Second, adding additional states increases the number of parameters in the model while possibly not providing further insights, so I follow a parsimonious approach. See subsection 3.3 for a robustness check by estimating the baseline model with 2 and 4 states, all else equal.

[7] It may be that the relation between mortgage debt and house prices is bidirectional, as already shown in the empirical literature on housing. However, as the target in this model is to capture a state with both high housing prices and debt, disentangling possible reverse causality is not considered necessary.

[8] Alternative specifications are also checked for robustness in subsection 3.3.

which means that state transition probabilities are time-varying and a function of the mortgage debt dynamics, which does not seem like a heroic assumption (Geanakoplos, 2009; Mian and Sufi, 2014, 2018; Stein, 2021).

A second model is also estimated adding a securitization dummy Sd_t proxying explosive growth in securitization. The rationale is that securitization might be a further driver of mortgage debt and house prices, therefore relevant in pinning down housing market states, as shown extensively in empirical literature (see Mian and Sufi, 2009, 2022 and Maddaloni and Peydró, 2011). Therefore, model (2) yields:

$$HP_t = \beta_{0,s} + \beta_1 W_t + \beta_2 E_t + \beta_3 R_t + \beta_{4,s} D_t + \beta_5 Sd_t + \varepsilon_t \tag{22}$$

where Sd_t is a state-independent variable dummy of real estate loans securitized. To compute this series, first I perform a SADF mildly explosive behavior test (see Phillips et al., 2015) on the real estate loans securitized during the baseline estimation sample. The output of that test is a series of augmented Dickey-Fuller test statistics (ADF) and critical values which are used as follows. The securitization dummy Sd_t is defined such that:

$$Sd_t = \begin{cases} 1 & \text{if } ADF_{S_t} > cv_{S_t} \\ 0 & \text{otherwise} \end{cases} \tag{23}$$

where ADF_{S_t} and cv_{S_t} are the corresponding t-statistic and critical values, respectively. Therefore, Sd_t is 1 when there is mild explosiveness in such time series and 0 otherwise. The rest of model (2) is unchanged with respect to the baseline model (1).

3 Empirical results

3.1 Markov switching model of housing boom fueled by credit

Table 1 shows the estimated coefficients of the three states Markov switching models specified in the previous section, where column (1) refer to the baseline specification and (2) correspond to the model including the securitization dummy S_d[9]. Regarding model (1), the following features are well noticeable. First, the state dependent elements in the estimation are statistically highly significant. Second, the three states dependent coefficients of mortgage debt outstanding growth are positive, suggesting that an increase in such variable has a positive effect on housing prices growth independently of the state. Third, the constant in state 2 is the only one having a positive coefficient, so giving a first hint that state 2 may be understood as a housing boom state. Fourth, the constant in state 3 is negative and far more negative than the constant in state 1, which suggest that state 3 may be a burst state. Therefore, it turns out that state 1 could be understood as normal times. Fifth, the coefficients of employment and rents are positive and highly statistically significant, while the coefficient of wages is not. With regard to model (2), the securitization dummy is statistically significant and slightly negative. This may be a consequence of the binary nature of the dummy variable, which is unable to capture the similar trends that housing prices and securitization followed during the considered time period[10].

The filtered Markov switching probabilities of being in each state are shown in Figure 1, in which the dashed red line corresponds with the baseline model (1) probabilities, and the solid red line refers to model (2)[11], i.e. including securitization. As already previewed in the previous paragraph further upheld later in this subsection I argue that the identified three states may correspond with *normal times*, *housing boom fueled by credit* and *implosion*, respectively. According to this correspondence, there appear four episodes of housing booms fueled by credit[12]. First, one in the late 80s, from January 1986 to February 1987. Second, a long episode in the preceding boom before the Great Recession, from February 2000 to February 2006. Third, a short period from June 2009 to May 2010. Fourth, a discontinuous case from March 2012 to May 2018. Interestingly, when controlling for securitization, the last boom is shortened in such a way that the period between 2014 and 2018 is mainly classified as being *normal times*. Moreover, the *implosion* state identified by model (1) in 1990 turns out to be *normal times* when adding securitization.

[9] This Markov-switching model is estimated using the regime switching toolkit of Ding (2022).

[10] For instance, from June 1996 to August 2009, when the securitization dummy is always one, housing prices growth shows a positive path only until the mid-2006.

[11] The smoothed Markov switching probabilities according to model (1) and (2) are shown in Appendix B.

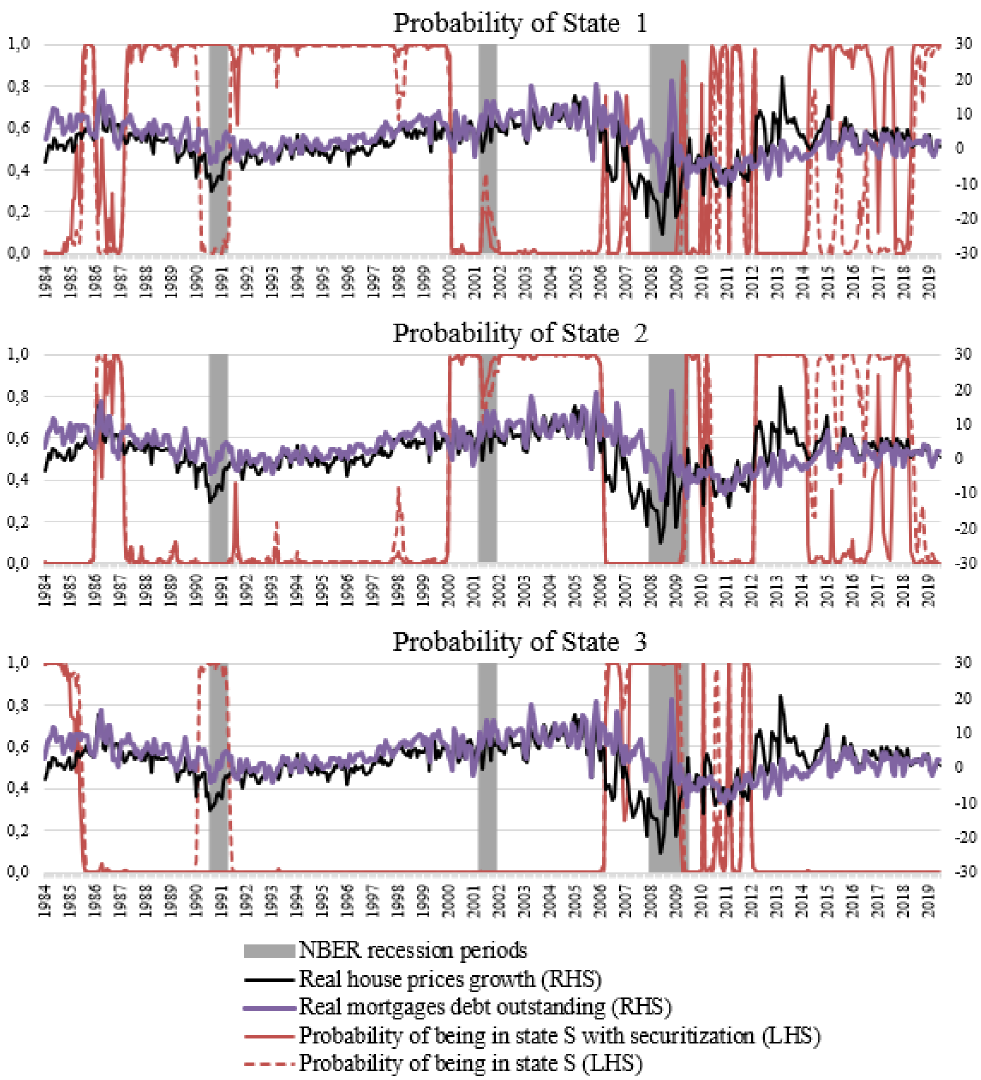
[12] A specific and commonly agreed definition of housing booms and credit booms is rather missing in the literature, where typically such empirical definitions are quite ad-hoc. For instance, Crowe et al. (2013) define a real estate boom as a period in which real house price appreciation is above a threshold of 1.5 percent or the annual real house price appreciation rate exceeds the country-specific historical annual appreciation rate. Also, they define a credit boom as a period in which the growth rate of bank credit to the private sector in % of GDP is more than a 20 percent or it exceeds the rate implied by a country-specific, backward-looking, cubic time trend by more than one standard deviation. Later in this section I provide evidence that during state 2 both housing prices and mortgage credit grow significantly over the average in the full sample, and also significantly more than in states 1 and 3.

Table 1: Markov switching model estimates.

	(1)		(2)	
Mean parameters				
Constant, state 1	-0.002***	(0.00)	-0.002***	(0.00)
Constant, state 2	0.002***	(0.00)	0.004***	(0.00)
Constant, state 3	-0.007***	(0.00)	-0.008***	(0.00)
Wages (W)	0.006	(0.01)	0.006	(0.02)
Employment (E)	0.609***	(0.07)	0.907***	(0.07)
Rents (R)	0.385***	(0.04)	0.549***	(0.05)
Mortgage debt (D), state 1	0.538***	(0.03)	0.592***	(0.05)
Mortgage debt (D), state 2	0.396***	(0.05)	0.361***	(0.06)
Mortgage debt (D), state 3	0.632***	(0.09)	0.592***	(0.09)
Securitization (S_d)			-0.001***	(0.00)
Variance parameters				
Constant, state 1	0.000***	(0.00)	0.000***	(0.00)
Constant, state 2	0.000***	(0.00)	0.000***	(0.00)
Constant, state 3	0.000***	(0.00)	0.000***	(0.00)
Time Varying Transition Probabilities				
p(1,1)(1)	1.547***	(0.24)	1.769***	(0.22)
p(1,1)(2)	143.77***	(64.17)	137.802***	(67.37)
p(1,2)(1)	-1.927***	(0.27)	-1.673***	(0.26)
p(1,2)(2)	-43.278	(71.68)	-60.552	(54.58)
p(1,3)(1)	-1.385***	(0.33)	-1.375***	(0.35)
p(1,3)(2)	-88.847	(69.35)	-104.687	(71.02)
p(2,1)(1)	9.897	(137.77)	10.332	(116.69)
p(2,1)(2)	2458.828	(3.4e+4)	2459.203	(28531.2)
p(2,2)(1)	1.993***	(0.32)	2.083***	(0.41)
p(2,2)(2)	35.685	(62.47)	19.267	(66.75)
p(2,3)(1)	-2.231	(1.87)	-2.123	(1.99)
p(2,3)(2)	-150.701	(466.25)	-137.059	(459.70)
Final Log likelihood value	2002.43		1994.11	
Akaike Information Criterion	-3.96e+03		-3.94e+03	
Bayesian information criterion	-3.86e+03		-3.84e+03	
Number of estimated parameters	24		25	

Notes: Standard deviations between brackets. Significance levels at 1%, 5% and 10% are represented by ***, **, * asterisks. Standard errors calculated using the first partial derivatives of the log likelihood, i.e. the outer product matrix. Model (1) is the baseline and model (2) adds a securitization dummy.

Figure 1: Filtered Markov switching probabilities of being in each state.



The latest transition probabilities matrix of model (2) is presented in Table 2[13]. These results show that once in any of the three states the most likely subsequent outcome is to remain in the same state, while the probability of jumping from state 1 to state 3 is very close to zero, which seems reasonable.

Table 2: Latest transition probabilities matrix, model (2).

		State in t-1		
		1	2	3
State in t	1	0.98	0.04	0.05
	2	0.02	0.95	0.01
	3	0.00	0.02	0.94

[13] Additionally, the latest transition probabilities matrix of model (1) is shown in Appendix C.

Table 3 shows the expected duration in each state for each of the two estimated models. Consistent with Figure 1, the expected duration of *housing booms fueled by credit* in a model with securitization is lower, while the expected duration of *normal times* is higher, whilst in the case of the *implosion* state it remains quite similar.

Table 3: Expected duration in each state.

	(1)	(2)
State 1	19.80	30.11
State 2	24.29	18.60
State 3	13.09	12.63

Notes: Expected duration is expressed in the number of time periods, which is the expected number of months.

To further investigate the nature of the three estimated states of housing market psychology, Table 4 exhibits the average growth rates of some macroeconomic and financial variables depending upon the state in which the economy is estimated to be according to the results of the baseline model (except interest rates and unemployment rate, that are in averaged levels). These calculations correspond to the Markov-switching model results with smoothed probabilities, while the differences with respect to the filtered estimation are negligible. The following observation are drawn from these results. First, real house prices growth is positive for both *normal* times (state 1) and *housing booms fueled by credit* (state 2), being much larger in the latter case. Alternatively, it sharply decreases during *implosion* times (state 3). Second, rental prices show a markedly different path. Indeed, rents growth is positive in the three states, exhibiting a smooth increase close to the full sample average growth rate. Third, the standard housing demand fundamentals also exhibit a relatively smooth and positive growth during the three states, exhibiting the highest expansion amid *normal* times and *housing booms fueled by credit*.

The fourth observation is that financial variables such as mortgage debt growth and interest rates exhibit the most expansionary tone during *housing booms fueled by credit*, when mortgages grow at its fastest rate and interest rates are at its lowest levels. Additionally, we can observe that real estate loans securitized grow at the fastest pace during *normal* times, while they decrease amid *implosion* times. Fifth, looking at the macro variables, we observe a contractionary behavior in industrial production, sales and the unemployment levels. This interpretation turns out to be consistent with public policy figures that exhibit a counter-cyclical pattern, such that public expenses grow the most during the *implosion* state, while tax revenues decline, forcing to the highest increase in public debt. This interpretation is also consistent with the current account balance, which deteriorates during normal and booming states, and improves during *implosion* times.

Finally, real estate indicators clearly exhibit an expansionary behavior during *housing booms fueled by credit* and a markedly negative one amid the *implosion* state, with declines in housing starts, new building permits, houses sold, new homes under construction, cement production, and accumulation of houses supply. Overall, these descriptive statistics are consistent with interpreting state 1 as being *normal* times, state 2 resembling *housing booms fueled by credit* and state 3 being *implosion* times. Indeed, these results are consistent with the theoretical predictions of Martín and Ventura (2018) and their previous contributions regarding the booming behavior of output, consumption, investment, asset prices, wealth and the current account during bubbly states.

Table 4: Summary statistics in each state: growth averages (%).

	Full Sample	State 1	State 2	State 3
Housing prices				
Real S&P Case-Shiller home price index	0.11	0.06	0.47	-0.53
Real urban primary residence rent index	0.06	0.02	0.09	0.08
Housing demand fundamentals				
Non-farm employees	0.12	0.18	0.09	0.05
Real wages	0.18	0.27	0.16	0.01
Working age population (aged 15-64)	0.08	0.07	0.08	0.08
Financial variables				
Real mortgages debt outstanding	0.27	0.23	0.33	0.24
30-year mortgage fixed rate average*	7.06	8.01	5.57	8.13
Fed funds*	3.79	4.94	1.96	5.19
Real real estate loans securitized	0.25	0.64	0.00	-0.11
Macroeconomic variables				
Industrial production	0.17	0.33	0.13	-0.09
Real manufacturing and trade sales	0.21	0.33	0.24	-0.11
Unemployment rate*	5.97	5.90	5.90	6.29
Real government total expenditures	0.19	0.16	0.19	0.24
Real government current tax revenues	0.19	0.30	0.19	-0.06
Real public debt	0.43	0.36	0.38	0.71
Real balance on current account	0.03	-0.29	-0.89	2.79
Real estate indicators				
Housing starts	0.21	0.35	0.97	-1.75
New building permits	0.07	0.27	0.82	-2.02
New one family houses sold	0.23	0.49	0.88	-1.78
Supply of houses	0.34	0.07	0.13	1.42
New homes under construction	0.04	0.03	0.59	-1.17
Real cement production	0.09	0.18	0.36	-0.66

Notes: These are the average growth rates computed during each subset of data, except in the case of interest rates and the unemployment rate, in which they are the average of the variable in levels. Quarterly variables have been linearly interpolated to get monthly series.

3.2 Comparison with alternative overvaluation signals

After defending the interpretation of the three states in the Markov switching model, in this subsection I focus the attention on the second state, i.e. *housing booms fueled by credit* with filtered probabilities, and compare the results with alternative approaches. To that purpose, I first construct measures of housing price overvaluation using two dynamic common factor models to proxy for housing demand and supply overvaluation, which hopefully may enrich the interpretation on the overvaluation sources. The structure of the dynamic factor models is common for both specifications, and it is specified in detail in Appendix D. In a nutshell, I take few indicators of demand and supply and summarize them separately using a dynamic common factor model following an autorregressive structure of order two. Then, I define overvaluation from demand (supply) as being present when the house price growth rates exceeds that of the common factor of demand (supply).

Second, I compare my results with those provided by researchers using mildly explosive behavior tests to identify bubbles in house prices, along the lines of Phillips et al. (2011, 2015). Among that literature, I mostly focus on Shi (2017) and Fabozzi et al., (2020) given that they do not rely on a price-fundamental ratio to test for exuberance, but instead test the residual of an estimation using several fundamentals. However, it has to be highlighted a key caveat: these authors try to find housing bubbles while in this paper I defined a model to find housing booms fueled by credit, instead. That said, Figure 2 plots again the probabilities of being in a *housing boom fueled by credit* (state 2, red lines), together with the overvaluation signals (i.e. the gray areas) according to demand (top graph) and supply side (middle chart) dynamic common factor models and the mildly explosive behavior test results of Shi (2017) in the bottom graph (brown area).

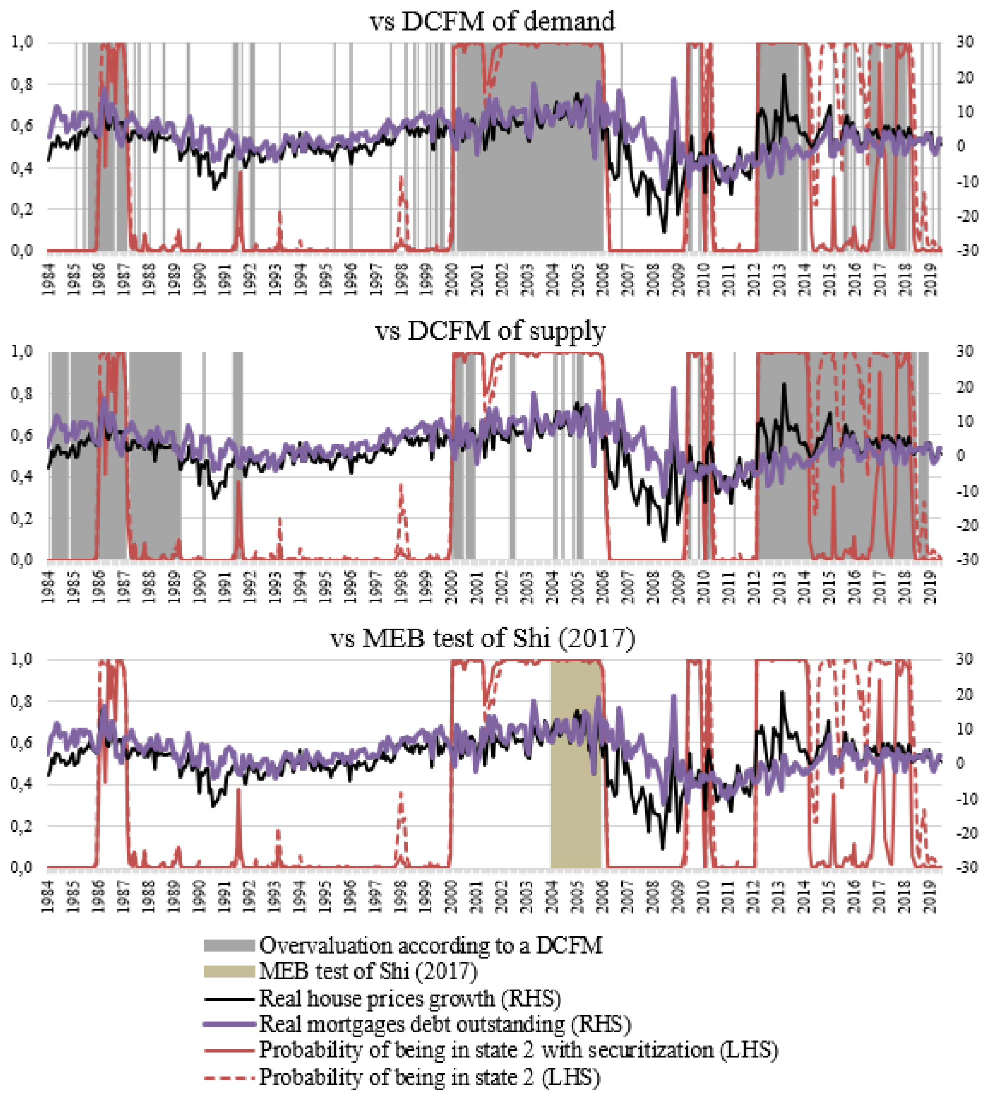
As reported earlier in this section, the largest *housing boom fueled by credit* emerges from February 2000 to February 2006, corresponding to the years previous to the Global Financial Crisis. The overvaluation signals point to a role played by demand factors to push such housing boom. These results are consistent with the literature, which widely interprets the housing boom of the 2000s as the result of booming demand fostered by credit (see Duca et al., 2010; Favara and Imbs, 2015; Di Maggio and Kermani, 2017; Adelino et al., 2018; *inter alia*). The dating of such housing boom fueled by credit period is along the lines of the findings of some researchers testing for housing bubbles using both user cost econometric models (Muellbauer, 2012) mildly explosive behavior tests (Shi, 2017; Fabozzi et al., (2020); Coulter et al., 2022; Pavlidis, 2022) and regime-switching techniques (Nneji et al., 2013; Whitehouse et al., 2022). Interestingly, Shi (2017) identifies a housing bubble from 2004 S1 to 2005 S2, which coincides with the final two years of this *housing boom fueled by credit*, which turns out to support the introduction of macroprudential policy during housing booms fueled by credit to smooth the housing cycle.

Previously, there appears a *housing boom fueled by credit* from January 1986 to February 1987, which is consistent with Nneji et al. (2013). In this period there are overvaluation signals both from the demand and supply side common factor models, while the nationwide mildly explosive behavior test of Shi (2017) is silent. However, this author finds bubble behavior in some US regional markets in the late 80s, giving some support to the Markov switching findings[14]. Along these lines, several authors suggested that the late 80s housing boom was related to technical change in key service industries together with consequential employment developments (Ball, 1994), an

[14] Shi (2017) identifies mildly explosive behaviors in bubble residuals in seven metropolitan areas such as Boston, New York, Philadelphia, San Francisco, Los Angeles, Honolulu, and Seattle in the late 80s.

expansion in private debt (BIS, 1992), extrapolative house price expectations (Poterba, 1991) and housing supply inelasticity (Glaeser and Gyourko, 2018).

Figure 2: Housing booms fueled by credit.



More recently, a *housing boom fueled by credit* arises from March 2012 to April 2014, signal where both baseline and extended models coincide. In this period there are also signals of overvaluation from demand and supply, while the explosiveness test of Shi (2017) is silent. Indeed, inelastic housing supply providing less than demanded housing is a common reading of this period (Rappaport, 2016; JCHS Harvard, 2018, among others).

Finally, a short and discontinuous *housing boom fueled by credit* pops up from June 2009 to May 2010, a period characterized by a stimulus-supported recovery in the US post-Global Financial Crisis (IMF, 2010) in which housing prices were stabilizing and credit conditions were attractive amid a still weak labor market. Therefore, this might be considered strictly as a false signal coming from a housing sector stabilization. Indeed, there are no signals of overvaluation neither from demand, nor from supply. Distinguishing between a boom and a fast recovery is ex-ante a difficult task, as we have recently witnessed in the post-pandemic housing boom.

Overall, the results found in this paper turn out to be consistent with those available in the literature, providing a further case for macroprudential action given that the underlying model does not target housing bubbles, but actually *housing boom fueled by credit*. As it is shown in the next section, the identification of such housing market psychology states can be exploited to define a macroprudential policy rule.

3.3 Robustness checks

To confirm the robustness of the results obtained in subsection 3.1, I estimate and report some alternative model specifications in this subsection[15]. First, I estimate model (1) and model (2) by using a different series of housing prices growth, i.e. the *nationwide house price index for existing single-family houses* issued by the FHFA (see Table 6). Both models (1) and (2) deliver similar results, however the distinction between *normal times* and *housing booms fueled by credit* becomes less clear, as there appear multiple changes of state.

Second, to mitigate the risk that considering different time intervals may bias the estimation of the Markov switching model, both model (1) and (2) are estimated using alternative time horizons. In particular, the models are estimated beginning in 1992 instead of 1984 in order to avoid an initial booming subperiod, and alternatively are estimated from 1984 to June 2007 to avoid the impact of the Great Recession. In all cases, the log likelihood is much lower than using the full data sample.

Third, the Markov switching model is also estimated using an alternative measure of income. In particular, using *real disposable personal income* instead of *real wages* (see Table 6) the results are analogous to those of the baseline specification.

Fourth, to verify the convenience of estimating the Markov switching model (1) with 3 states, I estimate it also with 2 and 4 states, all else equal. When the number of states are 2, one of the states agglutinates the *normal* and *implosion* states, while the other state proxies the standard *housing booms fueled by credit*. Therefore, choosing 2 states generates an information loss. Alternatively, when the number of states is set to be 4, one of the states is silent, while the difference between *normal times* and *housing booms fueled by credit* is less robust. So, there is no gain in this case either.

Fifth, I estimate the Markov switching model (2) using a different measure of securitization, such that the variable *real estate loans owned and securitized* is in growth rates (see Table 6). The results obtained in this case are similar to the baseline model (2).

Sixth, I add to the baseline model a measure of house price growth expectations proxying for an adaptive price expectation mechanism, along the lines of Duca et al., (2012), assuming that it might overshoot housing demand and in turn house prices beyond fundamentals. This is performed including a 1, 2, 3 or 4 years of house price growth lag(s) of the baseline house price series as a state-independent variable. This exercise does not improve the estimation of probabilities of being in any particular state as the interpretation of the results becomes unclear, while in some cases one of the three states becomes silent. Therefore, these results support not including house price expectations in the baseline Markov switching model.

[15]The results of these robustness checks are available upon request.

4 Counter-cyclical macroprudential policy

In this section I use the results obtained previously on the probabilities of being in each housing market state to define a policy rule for setting state-contingent macroprudential policy. In particular, I employ a rule structure that can be easily adapted to different policy tools, and set a hypothetical *sectoral counter-cyclical capital buffer (SCCyB)* and home mortgage interest deduction (HMID) rules. The former is an additional capital requirement that central banks can request individual banks to have as a buffer against a sectoral risk, where I focus the attention on housing booms fueled by credit risks, i.e. I am setting a housing SCCyB. While there is no general agreement on how to drive such a tool, it seems that active central banks set the general CCyB as if it was actually a housing SCCyB (Döme and Sigmung, 2023). For setting the broad CCyB, the usual candidate driver, i.e. the credit-to-GDP gap, is subject to several implementation challenges (see Babic and Fahr, 2019). Secondly, I adapt the policy rule structure to set a time-varying home mortgage interest deduction, which would be directly applicable to mortgaged households. Instead, this policy is a competence that belongs to national governments and that is typically left time-invariant, which spots a macroprudential chance as well as an opportunity to make public revenue and build fiscal resilience. This policy might also help overcome the limitations that banking regulation might face due to regulatory arbitrage.

The general structure of the counter-cyclical macroprudential policy rule is as follows:

$$Y_t = \phi_1 \cdot Y_{t-1} + \phi_2 \cdot [P(S=N)_t \cdot c_N + P(S=HBFC)_t \cdot c_{HBFC} + P(S=B)_t \cdot c_B] \tag{24}$$

where Y_t is the particular policy tool we are considering, i.e. the SCCyB or the HMID, ϕ_1 and ϕ_2 are smoothing parameters that sum up to one, $P(S=N)_t$, $P(S=HBFC)_t$ and $P(S=B)_t$ are the probabilities of being in normal times, housing booms fueled by credit and busts, respectively, estimated in each month t by the Markov switching model (2) shown in the previous section. Additionally, c_N, c_{HBFC} and c_B are the policy tools target levels chosen for each of the three states, respectively. The smoothing parameters ϕ_1 and ϕ_2 are common for both applications and are set equal to 0.9 and 0.1, respectively.

The rationale behind this formula is straightforward. First, it considers the problem of setting the macroprudential policy tool level as a classification problem in which first it has to be defined which is the state of the housing sector at each point in time. Second, I exploit the Markov-switching model of housing booms fueled by credit shown in the last two sections to pin down the probabilities of being in such state each month. Third, I define a macroprudential policy rule in which I plug such probabilities together with specific policy tool targets assigned to each state, which are adjustable to different policy tools of interest. In particular, a positive parameter c_N implies a positive cycle-neutral policy level (Arbatli-Saxegaard and Muneer, 2020). Fourth, the policy rule includes smoothing parameters that governs the speed at which the currently calculated policy level adjusts to the contemporaneous state policy target.

Notice that the structure and the logic behind this policy rule can be applied to virtually any macroprudential policy tool one can think of. For that, a policymaker only needs to estimate which is the state of the economy related to the financial stability risk that wants to mitigate and the desired target policy level in each state.

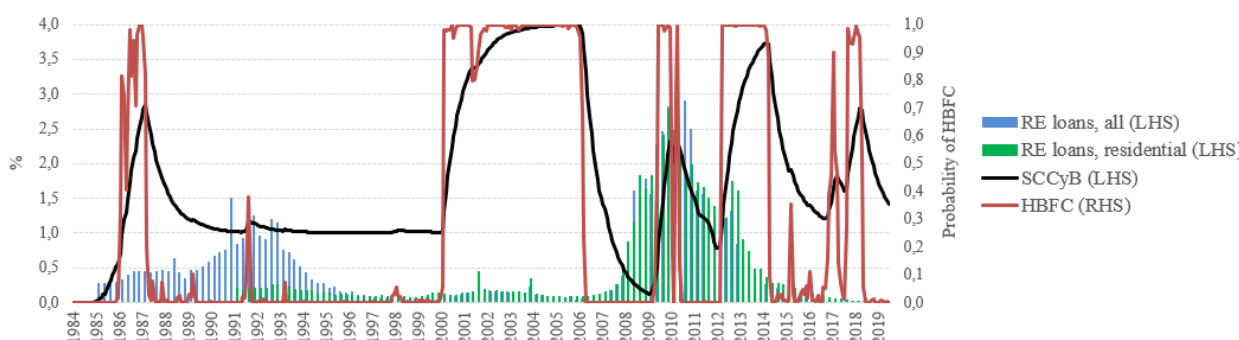
4.1 Sectoral counter-cyclical capital buffer (SCCyB)

After the Global Financial Crisis, a consensus on leaning against the wind emerged with regard to dealing with real estate booms and busts, despite the uncertainties around how to implement it. Requiring higher capital requirements to banks during good times was one of the proposals, that crystallized in the form of the *counter-cyclical capital buffer (CCyB)*, introduced in 2012. Later, given the fact that the CCyB could be too broad to deal with sectoral developments, the BIS (2019a, 2019b) launched a sectoral version of the CCyB, i.e. the *sectoral CCyB (SCCyB)*. This latter policy tool is a natural candidate to be exploited in the context of housing booms fueled by credit risks. In fact, there is evidence that capital requirements are effective in containing both credit and house prices (Ampudia et al., 2021).

As predicted in macroprudential policy literature, the expected outcome of this additional capital requirement for the banking system is twofold. First, it might prevent the build-up of housing booms and also the leverage boom of households and banks. Second, it might also improve the resilience of the banking sector in case that a bust realizes. To that purposes, the housing SCCyB policy rule is set by taking equation (24), plugging the probabilities of being in each housing market state as provided by the Markov-switching model (2), and adding the additional capital requirements targets in each state. In particular, I fix them as $c_N = 1\%$ (i.e. a positive cycle-neutral SCCyB), $c_{HBFC} = 4\%$ and $c_B = 0\%$ in percent of the sectoral risk weighted assets (RWA), that is matching the lower and upper bounds suggested by the BIS (2019b), assuming the case of a specialized bank and a contemporaneous broad CCyB requirement equal to 0%.

Figure 3 plots the SCCyB derived from the above formula (black line), together with the charge-off rates of real estate loans and the probability of being in a housing boom fueled by credit estimated by the extended Markov-switching model. Two observations emerge. First, periods of high charge-off rates on loans (during the early 90s and late 2000s) are preceded by years in which the policy rule estimates a high SCCyB, suggesting a leading and counter-cyclical behavior. Second, most of the times the SCCyB is around 1%, i.e. the additional capital requirement during normal times, which provides room for easing or tightening in case some unexpected shock materializes.

Figure 3: Sectoral counter-cyclical capital buffer (SCCyB) and charge-off rates on loans.



Sources: Own calculations and FRED data.
Notes: The left hand side scale represents the percentage with respect to sectoral RWA (SCCyB) or to total loans (charge-offs). RE refers to real estate.

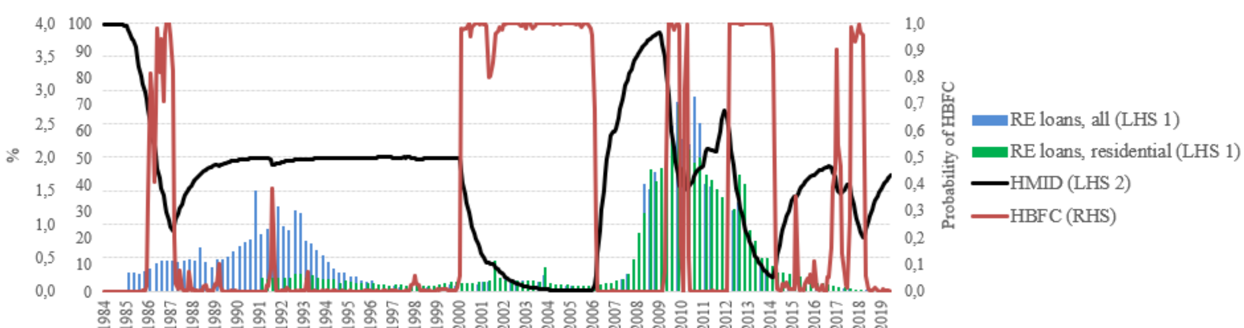
The advantages of the approach presented in this section with respect to hypothetically using the credit-to-GDP gap are the following. First, it targets specifically a housing fueled by credit as the risk to mitigate, with the corresponding implications in the modeling of the underlying Markov-switching model. Second, this approach avoids using GDP, which is subject to long delays and large revisions. Third, it avoids issues coming from the usage of the Hodrick-Prescott filter.

4.2 Home mortgage interest deduction

To set a time-varying home mortgage interest rate deductibility rule, I use the same general policy rule (i.e. equation (24)) and parameterize the policy target coefficients in each state for that specific policy tool. The rationale for proposing such tool is threefold. First, banks are sophisticated agents that might find ways to circumvent macroprudential policy rules. Targeting directly leveraged households, it might be possibly more difficult for this tool to be circumvented. Second, it allows governments to make macroprudential policy in case they consider that central banks are too lax in setting it. This might be specially important in large and heterogeneous jurisdictions. Third, by getting a revenue during booms, governments build a fiscal buffer that would be exploited in case a bust realizes. However, such benefits might be challenged by practical difficulties in implementation due to rigidities in the political sphere, specially in countries with a strong homeownership culture.

Figure 4 plots the HMID derived from the above formula (black line), the charge-off rates of real estate loans and the probability of being in a housing boom fueled by credit, where HMID is expressed in percentage of the total home mortgage interests paid by households. In this case, the parameterization is set assuming that in normal times households can deduct half of their mortgage debt service costs (c_N = 50%), however no deduction is available during booms (c_{HBFC} = 0%), while households can deduct all their mortgage debt costs during busts (c_B = 100%). In this way, HMID is time-varying and counter-cyclical, following the same pattern as the SCCyB in the previous subsection. Notably, HMID falls sharply in 2000 from 50%, reaching a level lower to 10% already in 2001 and 0% after 2004 until 2006, which correspond to the booming years previous to the Great Recession.

Figure 4: Home mortgage interest deduction and charge-off rates on loans.



Sources: Own calculations and FRED data.
Notes: The left hand side scale has actually 2 scales. LHS 1 (left) represents the percentage of the interest rate paid by borrowers that is deductible, while the LHS 2 (right) reflects the percent of charge-off loans with respect to the total loans of the banking system. MIR means mortgage interest rate and RE refers to real estate.

4.3 Would these policy tools help to prevent credit losses in the banking system?

To assess whether the two hypothetical tools computed in the previous subsections could have been helpful in smoothing the housing cycle possibly it should be tested in a structural model allowing for a housing and banking sector and macroprudential policy tools. Against this background, in this subsection I implement a forecasting exercise in which I evaluate the added forecasting ability of the SCCyB and HMID tools in predicting charge-off rates on real estate residential loans, which is arguably a crucial proxy of banking turmoil that a prudential policymaker would like to reduce to zero, or at least to some non-systemically important positive number close to zero.

To that purpose, I first build a benchmark model to forecast charge-off rates on real estate residential loans which is a FAVAR model that uses the 127 variables in the FRED-MD monthly dataset summarized by 7 factors, with data from February 1992 to June 2019. Additionally, I consider two augmented models, which add the policy tools SCCyB and HMID separately to the described FAVAR model. Then, I evaluate the forecasting performance of such three models up to 12 months ahead considering the subsample 2011 M1 - 2019 M6 as the evaluation sample. Table 5 exhibits the relative root mean squared error (RMSE) with respect to the benchmark model, i.e. the FAVAR model including only the 7 factors.

The main result from this exercise is that the inclusion of the SCCyB and HMID tools increase the forecasting performance of the benchmark FAVAR model with accuracy gains from 2% to 11%. These results suggest that such tools might be helpful in guiding macroprudential policy that could be potentiall implemented before banking losses actually materialize.

Table 5: Forecasting ability of the hypothetical SCCyB and HMID tools.

	Relative RMSE vs benchmark
Benchmark	
FAVAR 7F MP	1.00
Augmented models	
FAVAR 7F MP with SCCyB	0.98
FAVAR 7F MP with HMID	0.89

Notes: The FAVAR 7F MP is a monthly FAVAR model with 7 factors, Minnesota priors and 11 lags.

5 Discussion

The usage of the described Markov-switching model for identifying the states of the housing market psychology is subject to the following potential caveats. First, given a lack of data on the foreign housing demand, which is actually common to most (if not all) economies, I am not including such measure in the Markov-switching models. This additional source of demand might attenuate the overvaluation pressures captured by the model and labeled as housing booms fueled by credit. Secondly, in this analysis I am not providing an estimate on the size of overvaluation or undervaluation, as it is not the target of the Markov-switching model. In this regard, the results shown in this paper are complementary to other approaches available in the literature. Third, modeling the different states of the housing market endogenously would be a nice departure from the stochastic approach taken in this paper. However, this is also beyond the scope of this paper. One possibly useful analogy on that regard might be comparing the task performed in this paper to the problem tackled by the literature dealing with dating recessions and expansions by means of Markov-switching models as well. In both cases, we might explore endogenous mechanisms, but we believe that our classification problem is already well approached by exploiting a Markov switching model. In any case, in this paper I mitigate that possible criticism by allowing the transition probabilities from one state to another to be a function of mortgage debt growth.

Regarding the proposed structure of the counter-cyclical policy rule, the following caveats emerge. First, the chosen target policy levels are time-invariant and mostly speculative. An interested policymaker might better calibrate such targets by having access to credit register data. Second, the same applies to the smoothing parameters, that might be time-varying such that they require a higher or lower speed of adjustment depending upon additional data or the policymaker judgment.

6 Concluding remarks

The empirical evidence that relates excessive leverage, housing price growth and financial instability has accumulated since the Global Financial Crisis. As a result, new banking regulation emerged to reduce the likelihood of housing booms causing macroeconomic damage again. Theory suggests that policymakers might succeed in doing so, however they need at least two ingredients for an effective recipe. First, they need to know the housing market state at each point in time. Second, they need a state-contingent policy rule to implement the appropriate counter-cyclical policy on a timely basis. To date, there is no consensus among researchers and policymakers about how to deal with both issues.

In this paper I tackle such issues by using a regime-switching approach. First, I use a three states Markov switching model to estimate the probabilities of being in *housing booms fueled by credit*, normal times and busts. Secondly, I exploit such probabilities to feed a simple state-contingent policy rule, which I apply for setting a hypothetical housing counter-cyclical capital buffer (SCCyB) and a home mortgage interest deduction rule. Finally, I show that adding such tools improve the forecasting accuracy of a benchmark model in predicting charge-off rates on real estate residential loans. This suggests that the described approach might be useful in setting counter-cyclical policy able to deal with housing booms fueled by credit. However, further research is needed to assess that extreme in a structural model.

Future research along these lines may go in the following directions. First, it would be interesting to assess how the economy reacts to the implementation of macroprudential policies as proposed in this paper using a non-linear general equilibrium model with a housing sector. Second, the general policy rule used in this paper might be also used to drive other state-dependent macroprudential policy tools, such as the dividend distributions restrictions on banks, among others. Finally, the tools used in this paper might be replicated with alternative country data, for instance euro area and euro area countries data, some of which have been active in implementing macroprudential policy in recent years.

Appendices

A Data

Table 6: Time series data.

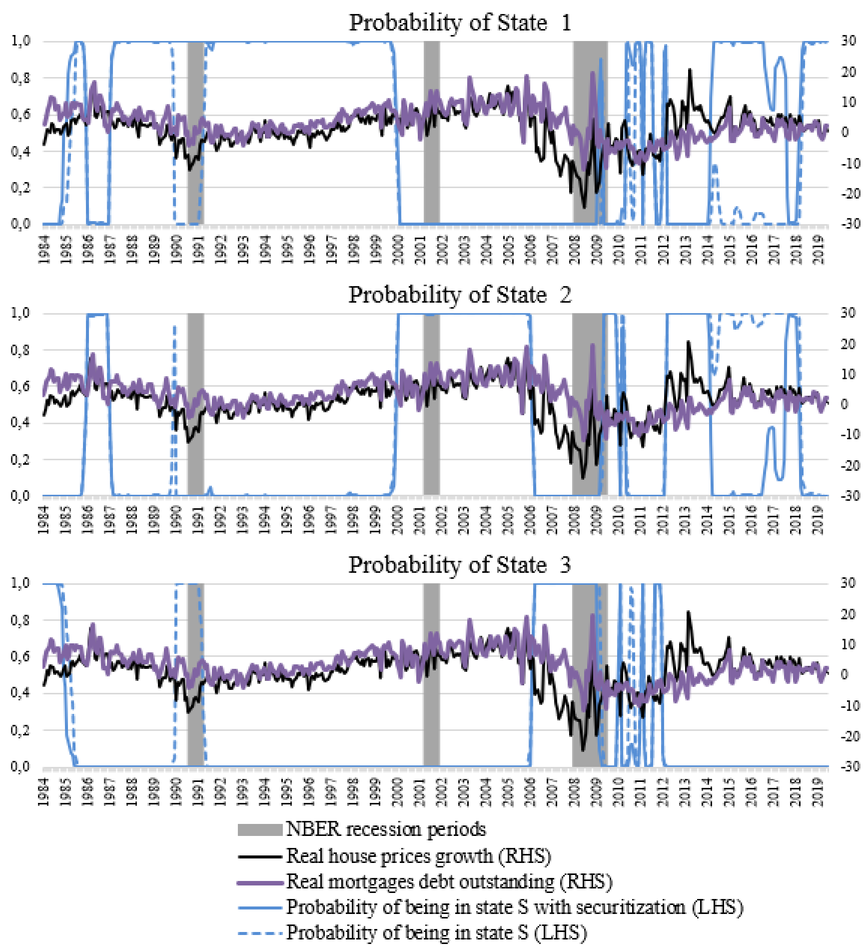
Variable	Acronym	Source	Data transformation
S&P Case-Shiller home price index	HP	S&P	R, L, D
Nationwide house price index for existing single-family houses	-	FHFA	-
Urban primary residence rent index	R	BLS	R, L, D
Working age population: aged 15-64	P	OECD	L, D
Employees, non-farm payrolls	E	BLS	L, D
Compensation of employees	W	BEA	R, L, D
30 year fixed rate mortgage average	F	FM	-
Balance on current account	C	BEA	M
Mortgage debt outstanding, all holders	D	BG	SA, M, R
Real personal income excluding current transfer receipts	I	BEA	L, D
Real estate loans owned and securitized	S	BG	R
New private housing building permits	B	CB	L, D
Housing starts	T	CB	L, D
New one family houses sold	N	CB	L, D

Notes: In the last column, *L* means that logs have been taken, *D* means taking one difference, *R* means that the variable has been transformed into real terms by applying the CPI, *M* means that the series have been transformed to a monthly frequency by linear interpolation. Regarding the sources of the data, S&P means Standard & Poor's, BLS means Bureau of Labor Statistics, BEA means Bureau of Economic Analysis, CB means the Census Bureau, BG stands for Board of Governors of the Federal Reserve System, BSL means Federal Reserve Bank of St. Louis, OECD stands for Organization for Economic Cooperation and Development and FM means Freddie Mac. FHFA stands for Federal Housing Finance Agency.

B Markov switching models: smoothed probabilities

The smoothed Markov switching probabilities of being in each of the three states according to model (1) and (2) are shown in Figure 5 (blue dashed and solid lines, respectively), where the interpretation of states is analogous to the one with filtered probabilities (detailed in subsection 3.1). Indeed, the results are quite similar after introducing the smoothing.

Figure 5: Smoothed Markov switching probabilities of being in each state.



C Markov switching model (1) results

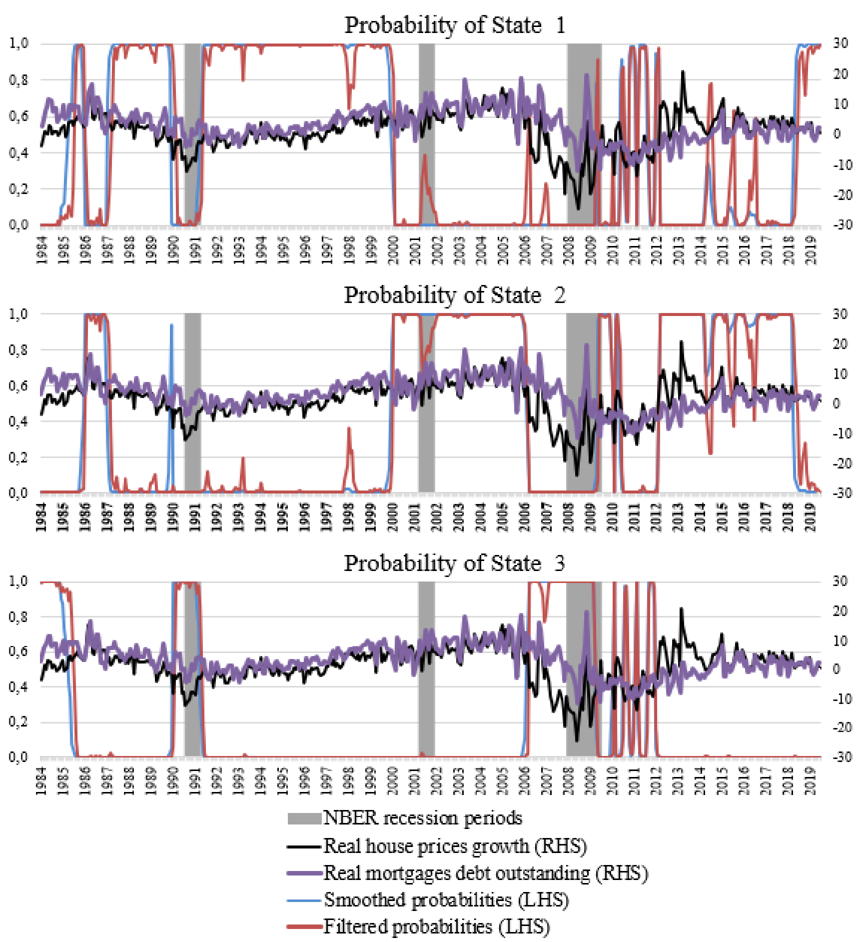
Table 7 shows the latest transition probabilities of the Markov switching model (1):

Table 7: Latest transition probabilities matrix, model (1).

		State in t-1		
		1	2	3
State in t	1	0.97	0.02	0.06
	2	0.03	0.96	0.00
	3	0.00	0.02	0.94

Figure 6 shows the comparison of filtered (red line) versus smoothed (blue line) Markov switching probabilities of being in each of the three states according to model (1).

Figure 6: Filtered and smoothed probabilities, model (1).



D Factor models of housing demand and supply

The structure of the dynamic factor models is common for both the demand and supply specifications. I assume first that housing demand and supply are better proxied by several indicators than taking one of them. Second, I assume that the included fundamentals in each of the models are reasonable proxies, as commonly used in the literature. Third, using the common factor implies that the comovements between the multiple time series in each model arise from a single common factor.

Let y_t denote an $i \times 1$ vector of housing fundamentals in stationary form and standardized, the dynamic common factor model of housing demand (or supply) yields:

$$y_t = \gamma c_t + e_t \tag{25}$$

where c_t is the common factor which follows an autorregressive structure of order 2 s.t.:

$$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + w_t \tag{26}$$

where $w_t \sim iid$ N(0, σ_w^2) and the errors $e_{i,t}$ in e_t above yield:

$$e_{i,t} = \psi_{i,1} e_{i,t-1} + \psi_{i,2} e_{i,t-2} + \varepsilon_{i,t} \tag{27}$$

where $\varepsilon_{i,t} \sim iid$ N(0, σ_i^2).

The selected housing demand fundamentals in log-differences are working age population (aged 15-64 years old), compensation of employees, non-farm employees and the CPI of rents of primary residence, which are standard measures of housing demand commonly used in the literature[16]. Alternatively, the factor model of housing supply include three variables in logs, which are new one family houses sold, building permits and housing starts, which are commonly used in the literature to track housing supply developments (see Hilbers et al., 2008).

Both housing demand and supply models are estimated using maximum likelihood, and the systems are updated by using the Kalman filter. After standardizing the common factor and applying the mean and standard deviation of log-differenced housing prices HP_t, we get the common factor of the fundamental variables in a housing prices-comparable fashion that we call f_t. Then, as deviations from house prices growth we get a measure of overvaluation O_t, such that:

$$O_t = HP_t - f_t \tag{28}$$

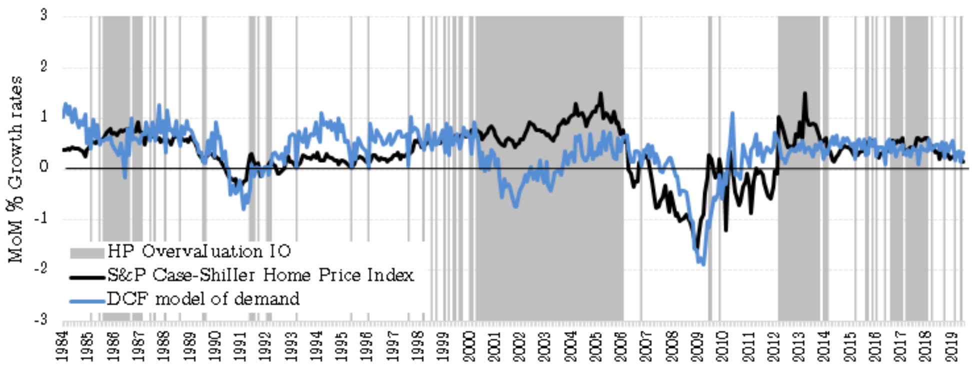
Finally, this time series of overvaluation O_t is used to generate a binary indicator of overvaluation IO_t such that:

$$IO_t(O_t) = \begin{cases} 1 & \text{if } O_t > 0 \text{ and } HP_t > 0 \\ 0 & \text{otherwise} \end{cases} \tag{29}$$

[16]See Girouard et al., (2006) for a review of studies on housing prices and fundamentals in OECD countries.

Figure 7 plots the dynamic common factor of housing demand (blue line) compared with the S&P Case-Shiller home price index (black line). According to this approach, the longest period of overvaluation corresponds to the 70 months from April 2000 to January 2006, i.e. the years before the Great Recession. Other periods of overvaluation are August 1985 to August 1986, March 2012 to October 2013 and from August 2016 to January 2018, discontinued in February 2017.

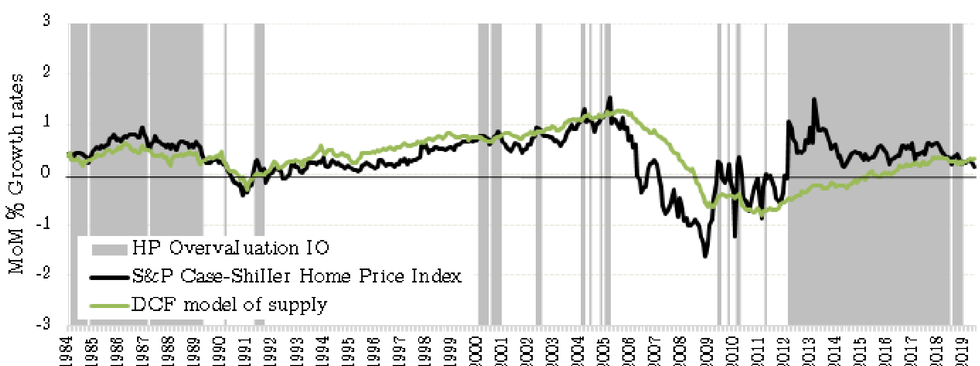
Figure 7: Common factor of housing demand and house prices.



Notes: The included housing demand fundamentals are *working age population (aged 15-64 years old)*, *compensation of employees*, *total non-farm employees* and *CPI of rents of primary residence*. The correlation coefficient between the demand factor and house prices is 44.3%.

Figure 8 exhibits the dynamic common factor of housing supply (green line). According to this setup, there are two periods of overvaluation, from January 1984 to April 1989 and from March 2012 until December 2018, both with some monthly discontinuities.

Figure 8: Common factor of housing supply and house prices.



Notes: The included housing supply proxies are *new one family houses sold*, *building permits* and *housing starts*. The correlation between the supply factor and house prices is 54.1%.

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