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Leaning against housing booms fueled by credit*

Carlos Cañizares Martínez†

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Abstract

This study aims to empirically identify the state of the US housing market and establish a countercyclical state-dependent macroprudential policy rule. I do so by estimating a Markov switching model of housing prices, in which mortgage debt affects house prices nonlinearly and drives state transition probabilities. Second, I propose a state-contingent policy rule fed with the probability of being in each state, which I apply to setting a housing countercyclical capital buffer, a mortgage interest deduction, and a dividend payout restriction. Finally, I show that such hypothetical tools contain early warning information in a forecasting exercise to predict the charge-off rates of real estate residential loans and a financial stress index. The significance of this study is that it informs policymakers about the state of the housing market mechanically, while also providing a general rule to implement a state-contingent and timely macroprudential policy.

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

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

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1 Introduction

The Global Financial Crisis and 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 (e.g., Cerutti et al., 2017b). A direct consequence of this realized turmoil was the introduction of new banking regulations to avoid the excessive build-up of credit risk. However, setting a macroprudential policy to mitigate housing boom-bust cycles, which might need to be nonlinear to achieve better economic stabilization (see Gatt, 2023), is still an open issue. In particular, the current methods for estimating housing price overvaluation and excessive credit do not seem fit for the job. Current approaches to monitoring housing booms often do not include mortgage debt in their models, neglecting a key reason for systemically dangerous housing overvaluation (Crowe et al., 2013; Jordà et al., 2015a). Additionally, the appearance of new policy tools typically carries uncertainty about how to implement them. Such threats might provide weak comfort to policymakers in implementing timely countercyclical policies, in turn giving room for *inaction bias*. In addition, electoral cycles may further dampen fiscal policymakers' incentives to actively deal with housing booms fueled by credit (Müller, 2022).

In the last decade, theoretical studies incorporating financial frictions and rich mortgage markets in macro models have investigated the mortgage credit channel of transmission (see Favilukis et al., 2017; Justiniano et al., 2019; Greenwald, 2018; and Guerrieri and Iacoviello, 2017, among others). New modeling devices such as collateral and lending constraints introduced in these models allow the generation of strong housing prices and credit boom-bust cycles that are consistent with those observed in the US and other countries during the 2000s. The nonlinearities inherent in these models around whether borrowing constraints are binding prescribe the usage of a nonlinear macroprudential policy (Guerrieri and Iacoviello, 2017; Gatt, 2023). However, before taking any action, policymakers must identify the current housing market state.

This study addresses this question by estimating a Markov switching model in which housing price growth is explained by standard housing demand fundamentals plus mortgage debt growth, which affects house prices nonlinearly and also drives the transition probabilities between each state. In doing so, I focus on identifying periods of *housing booms fueled by credit*, that is, states in which there is a high growth in house prices and mortgage debt once controlling for standard housing demand fundamentals[1]. In this way, I narrow down the search for this systemic risk source along the lines of Crowe et al., (2013). Thus, I distinguish between housing market states that allow for countercyclical and state-dependent macroprudential policies, as suggested theoretically by Gatt (2023) and empirically by Drehmann et al. (2010).

The described approach overcomes some key challenges faced by alternative methods for monitoring housing price development. First, the literature most often tries to find bubbles or explosive behavior in house prices, which is not necessarily a threat to financial stability because what makes a bubble systemically dangerous is being financed with debt (Jordà et al., 2015a). For this reason, bubble tests are not well-suited for macroprudential policy discussions. Second, the models used

[1] Alternatively, housing bubbles are usually defined along the lines of Stiglitz (1990), who establishes that "if the reason that the price is high today is only because investors believe that the selling price is high tomorrow—when 'fundamental' factors do not seem to justify such a price—then a bubble exists". Therefore, a bubble is fueled by beliefs or sentiments, whereas it does not make any explicit assumptions about the role of credit.

for this purpose are very stylized, leaving room for relevant variable omissions. Third, econometric models used for identifying overvaluation often provide inconsistent results (ESRB, 2022).

The contributions of this study are as follows. First, I provide a new empirical tool, namely, a Markov switching model, to identify the state of the housing market, focusing on identifying *housing booms fueled by credit* instead of asset price bubbles, thereby providing a stronger narrative for triggering a macroprudential policy. Second, I exploit the probabilities of being in each housing market state obtained in the regime-switching model to establish a rule for setting a sectoral countercyclical capital buffer (SCCyB)[2], mortgage interest deduction, and dividend payout restriction. Interestingly, such a policy rule structure is sufficiently general to be applied to other policy tools. Finally, I show that the results obtained by the proposed regime-switching model and policy rule contain useful early warning information about the soundness of banks' housing loans and financial risk in a forecasting exercise.

Related literature. This paper is related to several strands of the literature. First, this study's approach is motivated by empirical studies analyzing the effects of housing booms accompanied by credit booms on the economy and financial stability (Mian and Sufi, 2009, 2010, 2011, 2018, Jordà et al., 2013, 2015a, 2015b, 2016, 2017, Cerutti et al. 2017b, Greenwood et al. 2022, and Schularick and Taylor, 2012, among others). These studies document that credit booms tend to boost housing prices and, in turn, increase the risk of financial crises. Therefore, it is crucial for policymakers to monitor the housing market by focusing on identifying housing booms fueled by credit.

Second, this study is related to theoretical studies that model credit-driven housing booms using macro models. While the introduction of housing sectors in macro models arrived only in the 2000s, in recent years, additional features such as collateral and lending constraints have allowed modelers to generate realistic housing boom-bust cycles (see Favilukis et al., 2017 and Justiniano et al., 2019). Moreover, Guerrieri and Iacoviello (2017) find asymmetric effects in the relationship between house prices and economic activity owing to an asymmetry in the effects of collateral constraints. More recently, Gatt (2023) shows that occasionally binding borrowing constraints are a source of nonlinearity that warrants a nonlinear macroprudential policy. I follow this literature to motivate using a regime-switching model of housing booms fueled by credit.

Third, this analysis is also complementary to empirical studies measuring or dating periods of house price overvaluation, where there are 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 Phillips et al. (2011, 2015) propose, which exploits augmented Dickey-Fuller tests to find *exuberance* in asset prices. A third and relatively underused approach is to employ regime-switching models to date periods characterized by high or low prices (Van Norden and Schaller, 1993, 1996). Instead, this study focuses on housing booms fueled by credit, which I argue is better suited for setting macroprudential policy. Therefore, this study also relates to the household red-zone of Greenwood et al. (2022), which is an indicator of contemporaneous high household credit and housing price growth.

[2]As defined by the BIS (2019a), a sectoral CCyB is an additional capital requirement that "would require banks to build up a capital buffer on exposures to credit segments in which credit developments are deemed excessive."

Finally, this study also relates to the literature on macroprudential policies that deal with credit-driven housing booms. During the 2000s, there was no consensus on the appropriate policy response to housing booms (Bernanke, 2002; Roubini, 2006). The acute turmoil amid the Global Financial Crisis made it clear that better banking regulation would help mitigate systemic risks, namely via the so-called borrower-based measures (Aikman, 2021) and capital buffers (BIS, 2011, 2019a, 2019b). Despite being available to regulators for almost a decade, calibrating them remains challenging. For example, the countercyclical capital buffer (CCyB), in which standard suggestions on how to set it (BIS, 2010) do not seem to be widely followed (Döme and Sigmund, 2023).

The remainder of this paper is organized as follows. Section 2 presents the theoretical framework and the Markov switching model of housing booms fueled by credit. Section 3 describes the data and model specification and presents the empirical results. Section 4 proposes a general policy rule for setting a housing SCCyB, mortgage interest deduction, and dividend payout restriction by exploiting the estimated probabilities of each state using the Markov switching model. Section 5 assesses the early warning content of the estimated hypothetical macroprudential tools by evaluating their ability to predict banking losses in residential real estate loans and a proxy for financial risk. Section 6 discusses the significance of the results and the limitations of this study. Finally, Section 7 concludes.

2 Modeling housing booms fueled by credit

2.1 Theories of housing booms fueled by credit

Both empirical and theoretical research has highlighted the critical roles of financial accelerator effects and house prices in explaining the boom and bust of the 2000s that triggered the Great Recession. This subsection explores prominent theoretical frameworks that have emerged to elucidate the interactions among credit expansion, housing markets, and macroeconomic outcomes. The studies presented here serve as cornerstones for understanding the interplay of factors that contribute to the emergence and amplification of credit-fueled housing booms without being extensive, which motivates and builds the theoretical foundations of the Markov switching model of housing booms fueled by credit presented in this section.

The seminal paper in this literature, Iacoviello (2005), embeds mortgage debt and house prices into a New Keynesian DSGE model. This study integrates nominal household debt and a collateral constraint (Kiyotaki and Moore, 1997) tied to real estate prices into the DSGE model. The study reveals that demand shocks influence housing and consumer prices in the same direction, thereby amplifying them. The rise in asset prices enhances debtors' borrowing capacity, allowing them to spend more and invest more. An increase in consumer prices reduces the real value of outstanding debt obligations, which positively affects their net worth. Since borrowers have a higher propensity to spend than lenders, the net effect on demand is positive.

Building on this foundation, several studies have used this framework to analyze several features of the US boom and bust of the 2000s[3]. Favilukis et al. (2017) use a quantitative general equilibrium model with housing and collateral constraints to explore what drives fluctuations in

[3] See Guerrieri and Uhlig (2016) for a comprehensive survey of the literature.

house prices to rent ratio, introducing two new features not previously considered: aggregate business cycle risk and bequest heterogeneity in preferences. In this framework, the authors find that a relaxation of collateral requirements can generate a large boom in housing prices, while lower interest rates cannot explain housing booms. They also show that the key mechanism to generate a house price boom is a decline in housing risk premium, namely, the expected future housing return in excess of the interest rate.

To analyze the drivers of the US boom and bust in credit and housing prices that precipitated the Great Recession, Justiniano et al. (2019) use a DSGE model of household borrowing that features a lending constraint, a device to model the expansion in credit supply. The interaction between this constraint and the standard borrowing limit generates rich patterns of debt and home values that significantly improve the model's ability to match several fundamental facts observed during the 2000s' boom. In this way, they focus on looser lending constraints as drivers of the credit booms, consistent with the empirical works of Mian and Sufi (2009), Favara and Imbs (2012), and Di Maggio and Kermani (2014).

Similarly, Greenwald (2018) investigates the role of the *mortgage credit channel* of macroeconomic transmission in a DSGE model with loan-to-value and payment-to-income constraints. A novel propagation mechanism, namely the constraint switching effect, translates into large movements in house prices. This mechanism is active when there are changes in which the two constraints are binding for borrowers. Building on this framework, Greenwald and Guren (2021) analyze the role of credit in driving the 2000s housing boom using a DSGE model with arbitrary intermediate levels of rental markets frictions, thus avoiding taking an extreme modeling choice on the degree of housing supply elasticity. In such a framework, they find that in the US, between one-third and half of the increase in price-rent ratios during the 2000s was due to an increase in credit supply.

Guerrieri and Iacoviello (2017) also explore the relationship between house prices and economic activity in a nonlinear DSGE model, finding an asymmetry between them. They find that financial frictions in collateral constraints matter disproportionately more in a recession than in a boom, leading to asymmetric effects of housing booms and busts depending on whether housing collateral constraints are binding. This mechanism is fundamental for explaining the depth of the Great Recession.

More recently, Gatt (2023) shows that occasionally binding borrowing constraints are a source of nonlinearity that warrants a nonlinear macroprudential policy. Using a DSGE model, this author finds that an asymmetric macroprudential policy rule that lowers the borrowing limit more aggressively during credit booms obtains better economic outcomes than an optimized symmetric rule. Such an asymmetric policy response reduces output and inflation tail risks, generating better economic stabilization and positive externalities to monetary policy.

2.2 A Markov switching model of housing booms fueled by credit

The Markov switching model of house prices adopted in this study is an extension of Markov chains with time-varying transition probabilities, drawing from Hamilton (1989), applied in the housing sector. This model aims to identify different states in the housing sector, with a special emphasis on identifying housing booms fueled by credit. Many empirical (Mian and Sufi, 2009;

Cerutti et al., 2017b; Crowe et al., 2013) and theoretical studies (Guerrieri and Iacoviello, 2017; Justiniano et al., 2019; Greenwald, 2018) underline that this phenomenon plays a crucial role in explaining large boom-bust cycles and thus has strong implications for financial stability; therefore, policymakers must monitor their likelihood. Economic variables such as house prices and mortgage debt growth are a series that undergo episodes in which they seem to change dramatically, suggesting that a regime-switching approach to model housing booms fueled by credit is a promising venue. To that end, this section proposes a Markov switching model of housing booms fueled by credit that provides the probability of being in different housing states.

Let us define HP_t as the log-difference of the nationwide house price index in period t, X_t as a vector of variables whose effects on HP_t are state-independent, Y_t is a vector of variables whose effects on the dependent variable are state-dependent, and s_t is the latent state variable that defines the state of the housing sector in each period t such that:

$$HP_t = \phi_{0,s_t} + \phi_1' X_t + \phi_{2,s_t}' Y_t + \varepsilon_t \tag{1}$$

where $\varepsilon_t \overset{\text{iid}}{\sim} N(0,\, h_{s_t})$. For simplicity, let us assume that there are two states, denoted as 1 and 2, such that s_t = 1 or s_t = 2. Therefore, depending on the state, the state-dependent coefficients 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:

$$p_t = P(s_t = 1 | s_{t-1} = 1, \omega_t) \tag{2}$$
$$1 - p_t = P(s_t = 2 | s_{t-1} = 1, \omega_t) \tag{3}$$
$$q_t = P(s_t = 2 | s_{t-1} = 2, \omega_t) \tag{4}$$
$$1 - q_t = P(s_t = 1 | s_{t-1} = 2, \omega_t) \tag{5}$$

where ω_t is a vector of variables known in period t that affect the state transition probabilities in period t. Therefore, I am assuming that state transition probabilities are not constant, but time varying and dependent on a vector of economic variables. The parameters of this model are obtained by maximum likelihood estimation. See Appendix B for details on the estimation of the model.

3 Empirical results

3.1 Data

The sample size starts in January 1984, that is, avoiding possible issues arising from the structural break in aggregate volatility before the *Great Moderation*, and ends in March 2023. 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, it is a nationwide measure that fit the scope of this study. 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 used in this study are the fundamental drivers of housing demand and those related to housing finance. As part of the first block, I consider a measure of employment (*all employees: total non-farm payrolls*), wages (*gross domestic income: compensation of employees, paid: wages and salaries*), and housing rental prices (*CPI for urban consumers: rent of primary residence*), which are standard measures of income and purchasing capacity commonly used in the literature. In the second group of variables, I consider a measure of mortgage debt (*mortgage debt outstanding, individuals, and other holders*), which is interpolated to monthly frequency using Chow and Lin (1971) linear interpolation.

Additional variables are used for companion tasks, such as measures of housing demand (*working-age population*) and housing supply (*new one-family houses sold*, *new building permits*, and *housing starts*). Table 7 in the Appendix lists all of the time series used in this study, their sources, and the transformations performed.

3.2 Model specification

The Markov switching model of housing booms fueled by credit proposed in this study is a monthly model that features house price growth as the dependent variable and four explanatory variables, all of which are specified in quarterly growth rates. In particular, HP_t is the S&P Case-Shiller home price index in month t, whereas the independent variables are measures of wages (gross domestic income: compensation of employees, paid: wages and salaries, denoted by W), employment (all employees: total non-farm payrolls, denoted by E), and housing rental prices (CPI for urban consumers: rent of primary residence, denoted by R), which are fundamental variables of housing demand assumed to affect house prices growth homogeneously across states. Instead, mortgage debt outstanding (specifically, mortgage debt outstanding, individuals, and other holders, denoted by D) is a variable that affects housing prices nonlinearly, depending on the housing market state in each period[5]. Therefore, the Markov switching model is expressed as follows:

$$HP_t = \beta_{0,s_t} + \beta_1 W_t + \beta_2 E_t + \beta_3 R_t + \beta_{4,s_t} D_t + \varepsilon_t \tag{6}$$

where $\varepsilon_t \sim N(0, h_{st})$. I consider two specifications, Model 1 and Model 2, which are three- and four-state specifications such that $s_t = [1,2,3]$ and $s_t = [1,2,3,4]$, respectively. The choice to determine the number of states depends on two elements. First, it is assumed that a reasonable guess in modeling house price dynamics would suggest setting the minimum number of states equal to three, which may correspond to normal times, booms, and bursts. Second, statistical tests showed that adding a fourth state provides a better fit to the data (see subsection 3.3).

Further, the conditional variance of HP_t is given by:

$$\ln(h_{s_t}) = \lambda_{0,s_t} \tag{7}$$

[4] The house price index computed by the Federal Housing Finance Agency relies on 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).

[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).

The state-transition probabilities for the four-states specification (Model 2) are specified as follows:

$$p_t = P(s_t = 1 \mid s_{t-1} = 1, \omega_t) = \Phi(\pi_{0,p} + \pi_{1,p} D_t) \tag{8}$$
$$q_t = P(s_t = 2 \mid s_{t-1} = 2, \omega_t) = \Phi(\pi_{0,q} + \pi_{1,q} D_t) \tag{9}$$
$$z_t = P(s_t = 3 \mid s_{t-1} = 3, \omega_t) = \Phi(\pi_{0,z} + \pi_{1,z} D_t) \tag{10}$$
$$r_t = P(s_t = 4 \mid s_{t-1} = 4, \omega_t) = \Phi(\pi_{0,r} + \pi_{1,r} D_t) \tag{11}$$

where p_t, q_t, z_t and r_t are the probabilities of staying in the same state in period t, conditional on staying in the same state in the previous period and the information set ω_t, for states one, two, three, and four respectively. Thus, the transition probabilities across housing market states are time-varying and depend on mortgage debt growth, consistent with the target of identifying housing booms fueled by credit. In this way it is captured the notion of Mian and Sufi (2009), Di Maggio and Kermani (2017), Justiniano et al. (2019), Greenwald (2018), and Stein (2021), among others (see previous section), that credit can induce the appearance of large housing boom-bust cycles[6]. Implicitly, I am making two assumptions in this specification. First, the fundamental dynamics of house prices are well approximated by the standard fundamentals of housing demand and *dividends* such as wages, employment, and rent, which do not have a role in boom-bust state-dependencies. Second, the possible excess demand leading to boom-bust cycles is driven by mortgage debt.

3.3 Results

Table 1 shows the estimated coefficients of Models 1 and 2, that is, the three- and four-state Markov switching models specified in the previous subsection, respectively[7]. The following results stand out. First, state-dependent parameters are most often highly statistically significant. Second, the state-dependent coefficients of mortgage debt outstanding growth are positive, suggesting that an increase in this variable has a positive effect on housing price growth, independent of the state. Third, the constants in state 2 (Model 1) and states 2 and 3 (Model 2) are the only ones with positive coefficients, indicating that they may be booming states. Fourth, the constants in states 3 (Model 1) and 4 (Model 2) are negative and far more negative than those in state 1, which suggests that they may correspond to a burst state. Fifth, the coefficients of wages and rent are positive and highly statistically significant.

[6] The relationship between mortgage debt and house prices may be bidirectional, as already shown in the empirical literature on housing. However, because 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.

[7] This Markov switching model is estimated using the toolkit of Ding (2023). To initialize the filter, naïve values for the coefficients are chosen as follows: β_1, β_2, β_3 and β_5 are set equal to 0.5; $\beta_{0,s}$ and $\beta_{4,s}$ are set equal to zero; the diagonal transition probabilities in Model 1 (2) are set equal to 0.95 (0.925), and the off-diagonal transition probabilities are set equal to 0.025 (0.025).

Table 1: Markov switching model estimates.

	Model 1		**Model 2**	
Mean parameters				
Constant, state 1	-0.000	(0.00)	-0.004***	(0.00)
Constant, state 2	0.021***	(0.00)	0.025***	(0.00)
Constant, state 3	-0.019***	(0.00)	0.006***	(0.00)
Constant, state 4	-	-	-0.023***	(0.00)
Wages (W)	0.062**	(0.03)	0.134***	(0.02)
Employment (E)	0.013	(0.03)	-0.032*	(0.02)
Rent (R)	0.471***	(0.05)	0.157***	(0.04)
Mortgage debt (D), state 1	0.537***	(0.03)	0.617***	(0.02)
Mortgage debt (D), state 2	0.172*	(0.10)	0.064	(0.09)
Mortgage debt (D), state 3	0.498***	(0.08)	0.405***	(0.02)
Mortgage debt (D), state 4	-	-	0.753***	(0.11)
Log likelihood value	1705.78		1798.16	
Akaike Information Criterion	-3363.57		-3518.32	
Bayesian Information Criterion	-3263.85		-3356.28	
Number of estimated parameters	24		39	
Number of observations	471		471	
Number of states	3		4	

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. Variance parameters are not reported to save space, while they are all close to zero. Time-varying transition probabilities are reported in Appendix C.

A battery of statistical tests evaluates how the modeling choices in building the specified models fit the data, as summarized in Table 8 in the Appendix. First, a likelihood ratio test for the existence of three states versus two states rejects the null hypothesis in favor of the unrestricted model; in this case, a three-state model specification (Model 1). Furthermore, a likelihood ratio test for the existence of four states versus three states also rejects the null hypothesis in favor of the unrestricted model, thus supporting a four-state specification (Model 2). Second, likelihood ratio tests assessing whether the state-dependent coefficients are equal reject the null hypothesis of equal means, both regarding the constant (β_{0,s_t}) and the coefficient of mortgage debt (β_{4,s_t}) in equation (6), both in Models 1 and 2. A likelihood ratio test of equal variances across states (λ_{0,s_t}) also rejects the null hypothesis of equal variances for both models. The time-varying coefficient of mortgage debt growth on the probability of being in each state ($\pi_{1,p}$, $\pi_{1,q}$, $\pi_{1,z}$, $\pi_{1,r}$) is also tested using a likelihood ratio test, in which the null of equal effects across states is rejected for both models. Finally, a Goldfeld-Quandt heteroskedasticity test focusing on mortgage debt fails to reject the null hypothesis of homoskedasticity in both Models 1 and 2, thus suggesting that the errors are not related to mortgage debt growth.

Figure 1 plots the smoothed (solid red line) and filtered (dashed red line) Markov switching probabilities of being in each state according to Model 2. As previously mentioned and upheld later in this subsection, I argue that states 2 and 3 may correspond to booming states, while state 4 might correspond to *implosion*[8]. Notably, three booming episodes were identified in State 3. First, during the 2000s, from late 2003 to March 2006, that is, the years prior to the Great Recession. Second, there was a boom between April 2012 and April 2014. Finally, there was also a booming signal early after the Covid-19 pandemic hit, from August 2020 to June 2022. These three episodes appear to occur in times of highest real house price growth (black line) and match the probabilities of being in state 2 according to Model 1 (see Figure 4 in the Appendix). Times in which the probabilities of being in state 2 are high also correspond to episodes in which house prices and real mortgage debt outstanding growth (purple line) are booming, though at a slower speed than in state 3. Interestingly, the probability of being in state 2 was close to one during the early 2000s, from 2000 to 2004, hinting at early booming signals. In addition, it was high during the mid- 1980s and between 2014 and 2018. In contrast, the highest probabilities of being in state 4 correspond to episodes in which house prices declined heavily, such as in the early 1990s, the late 2000s during the Great Recession, and the post-pandemic slump in 2022. Alternatively, the high probabilities of being in state 1 coincide with years in which house price growth is close to zero and during the recovery of 2009–2012.

[8]A specific and commonly agreed upon definition of housing booms and credit booms is missing in the literature, where such empirical definitions are typically 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% or the annual real house price appreciation rate exceeds the country-specific historical annual appreciation rate. They also 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 20 % or exceeds the rate implied by a country-specific, backward-looking, cubic time trend by more than one standard deviation.

Figure 1: Markov switching probabilities of being in state s_t, Model 2.

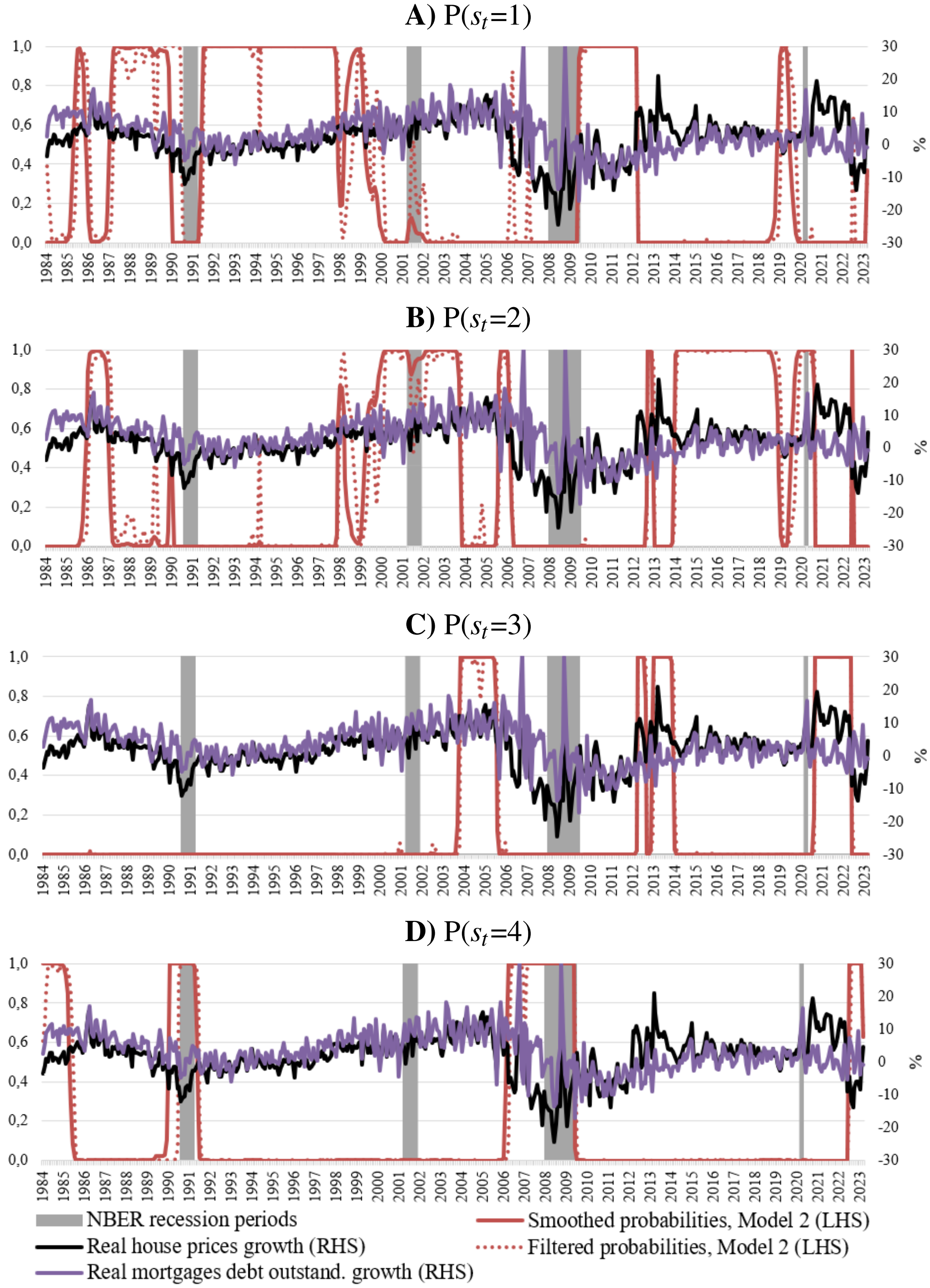


Table 2 presents the latest transition probability matrix for Model 2[9]. This shows that once in any of the four states, the most likely subsequent outcome is remaining in the same state. Moreover, when in state 2, the most likely alternative possibility is to move to state 3, which means moving from a booming state to another more exuberant state in terms of house price growth, as shown in Table 4. Furthermore, in implosion state 4, the only alternative to continue in the same state is to move to state 1, which is consistent with the idea that after an implosion, it is unlikely to transition immediately to a booming state again.

Table 2: Latest transition probabilities matrix, Model 2.

		State in T-1			
		1	2	3	4
	1	0.96	0.00	0.02	0.03
State in T	2	0.01	0.93	0.04	0.00
	3	0.02	0.07	0.91	0.00
	4	0.01	0.00	0.03	0.97

Table 3 presents the expected duration in each state for the two estimated models (see Hamilton, 1989). To calculate this, I assume that the probability of being in each state S is the average of the latest transition probabilities of being in state S estimated in each period t across all the time periods.

Table 3: Expected duration in each state.

	Model 1	**Model 2**
State 1	45.21	27.89
State 2	19.64	14.96
State 3	22.12	24.81
State 4	-	15.14

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 estimated housing market states, Table 4 shows the average growth rates of some macroeconomic and financial variables depending on the state in which the US housing market is estimated based on the results of Model 2 (except interest rates, which are on average levels). These calculations correspond to the Markov switching model results with smoothed probabilities, whereas the differences with respect to the filtered estimation are negligible. The following observations emerge from these results. First, real house price growth is positive and much higher than for the full sample average during states 2 and 3, while it is strongly negative in state 4 and close to zero during state 1. This suggests that states 2 and 3 correspond to housing price booms, whereas state 4 corresponds to bursts, and state 1 is a steady state. Second, it turns out that standard housing demand fundamentals develop in a relatively smoother fashion, thus suggesting that large swings in house prices should be driven by other forces. Third, mortgage

[9] Additionally, the latest transition probabilities matrix of Model 1 is shown in Appendix E.

debt grows at the highest speed during state 2, whereas it also grows at the full sample average or more during states 3 and 4. Moreover, mortgage rates and Fed funds are relatively lower in states 2 and 3. Finally, real estate indicators exhibit expansionary behavior during the booming states 2 and 3 and a markedly negative behavior amid *implosion* state 4, with declines in housing starts, new building permits, houses sold, new homes under construction, cement production, and accumulation of house supply. Other macro variables, such as industrial production, sales, and unemployment levels, also exhibit a contractionary tone during state 4. Overall, these descriptive statistics are consistent with interpreting state 1 as a steady state that includes normal and recovery times, state 2 and 3 as *housing booms fueled by credit*, and state 4 as *implosion* times. Regarding the difference between states 2 and 3, the latter exhibits a house price growth exuberance that seems beyond the development of both standard housing demand fundamentals and credit.

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

	Full Sample	**State 1**	**State 2**	**State 3**	**State 4**
Housing prices					
Real S&P Case-Shiller home price index	0.14	-0.03	0.39	0.83	-0.49
Real urban primary residence rent index	0.05	-0.01	0.13	-0.05	0.12
Housing demand fundamentals					
Non-farm employees	0.11	0.16	0.06	0.22	0.04
Real wages	0.17	0.22	0.20	0.14	0.04
Working age population (aged 15-64)	0.07	0.07	0.08	0.05	0.07
Financial variables					
Real mortgages debt outstanding	0.27	0.13	0.40	0.26	0.32
30-year mortgage fixed rate average*	6.76	7.74	5.75	4.36	8.41
Fed funds*	3.54	4.45	2.59	0.73	5.56
Real real estate loans securitized	0.16	0.48	0.22	-0.70	-0.02
Other macroeconomic variables					
Industrial production	0.14	0.33	0.05	0.27	-0.17
Real manufacturing and trade sales	0.20	0.35	0.18	0.23	-0.09
Real estate indicators					
Housing starts	0.26	0.48	0.60	1.24	-1.57
New building permits	0.12	0.43	0.65	0.71	-1.99
New one family houses sold	0.24	0.78	0.53	0.13	-1.39
Supply of houses	0.47	-0.49	0.55	2.14	1.08
New homes under construction	0.04	-0.11	0.58	1.31	-1.39
Real cement production	0.06	0.29	0.31	0.02	-0.90

Notes: Average growth rates computed for each subset of data, except in the case of interest rates, in which they are the average of the variable in levels. Full sample ranges from January 1984 to March 2023. The quarterly variables were linearly interpolated to obtain a monthly series.

3.4 Comparison with alternative overvaluation signals

In this subsection, I focus on booming states 2 and 3 and compare the results with those of alternative approaches. To this end, I first construct measures of housing price overvaluation using two dynamic common factor models to proxy for housing demand and supply overvaluation, which may enrich the interpretation of overvaluation sources. The structure of the dynamic factor models is common for both specifications and is specified in detail in Appendix F. In summary, I take a few indicators of demand and supply and summarize them separately using a dynamic common factor model following an autoregressive structure of order two. Then, I define overvaluation from demand (supply) as present when the house price growth rate exceeds that of the common factor of demand (supply).

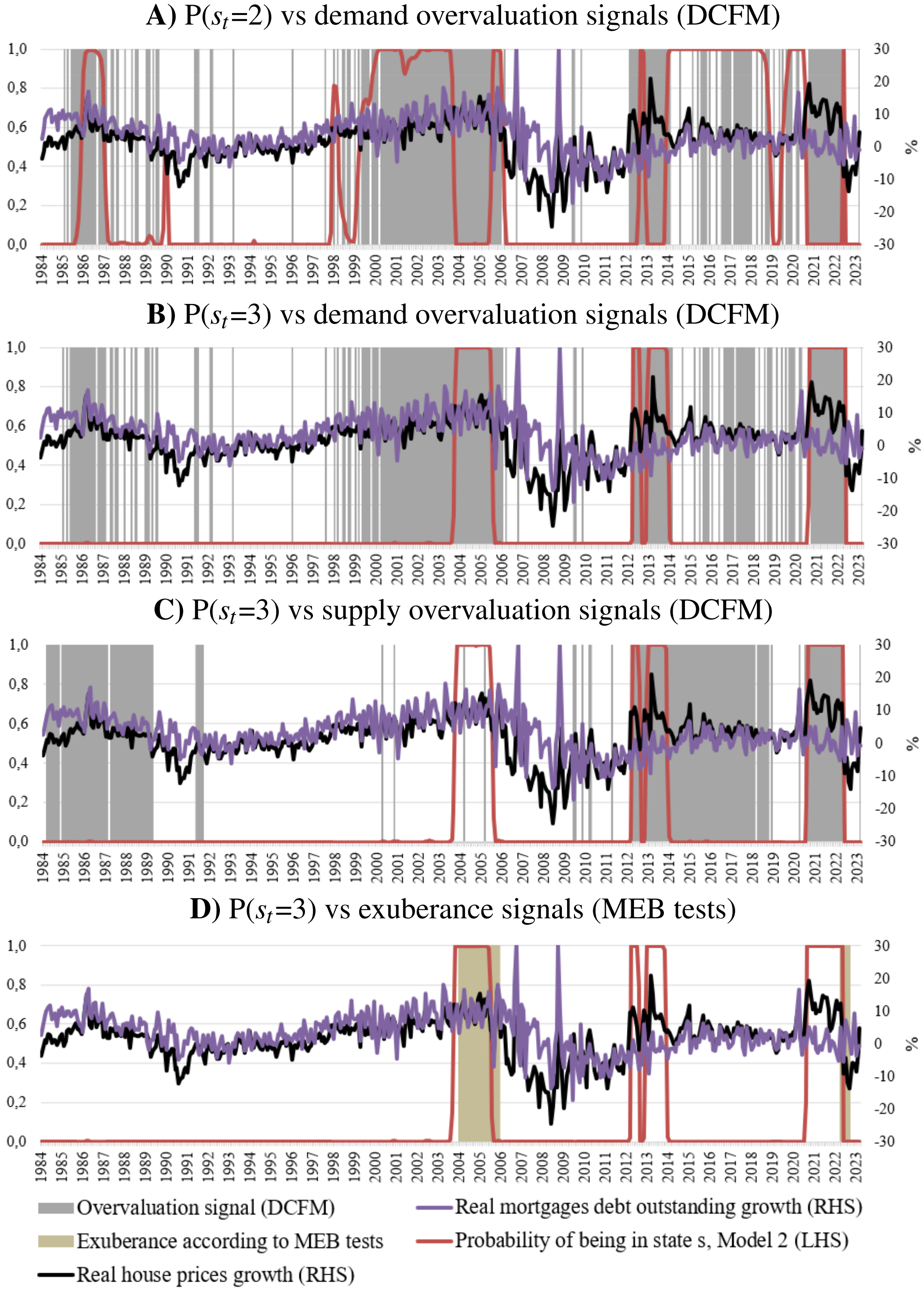
Second, I compare my results with those provided by researchers using mildly explosive behavior (MEB) tests to identify bubbles in house prices along the lines of Phillips et al. (2011, 2015). In the literature, I mostly focus on Shi (2017) and Fabozzi et al., (2020), given that they do not rely on a price-fundamental ratio to test for exuberance but instead test the residual of an estimation using several fundamentals. However, a key caveat must be highlighted: these authors try to find housing bubbles, while in this paper, I define a model to find housing booms fueled by credit. In other words, Figure 2 plots the probabilities of being in a *housing boom fueled by credit* (state 2 in graph A; state 3 in graphs B, C, and D), together with the overvaluation signals (i.e., the gray areas) according to the demand (graphs A and B) and supply side (graph C) dynamic common factor models, and the mildly explosive behavior test results of Shi (2017) in the bottom graph (brown area).

During the years prior to the Global Financial Crisis in the 2000s, Model 2 points to a high probability of being in state 2 from 2000 to 2004 and high probabilities of being in state 3 from 2004 to 2006. During this time span, overvaluation signals point to the role of demand factors in pushing such a housing boom. These results are consistent with the literature, which widely interprets the housing boom of the 2000s as a 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; and *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 et al., 2016), and regime-switching techniques (Nneji et al., 2013; Whitehouse et al., 2023). Interestingly, Shi (2017) identified a housing bubble from 2004 to 2005, which coincided with the final two years of this *housing boom fueled by credit*. Moreover, Greenwood et al. (2022) also find a household red-zone between 2002 and 2006 in the US, which coincides with high probabilities of being in states 2 and 3 in the Markov switching Model 2, while the latter started providing booming signals in 2000.

More recently, a *housing boom fueled by credit* emerged from March 2012 to April 2014. In this period, there were signals of overvaluation from demand and supply, whereas the explosiveness test of Shi (2017) was silent. Indeed, an inelastic housing supply providing less than demanded housing is a common reading of this period (Rappaport, 2016; JCHS Harvard, 2018, among others).

Finally, a *housing boom fueled by credit* emerged in August 2020 after the pandemic hit, which lasted until mid-2022, when real house price growth increased significantly. This booming signal is contemporaneous with both the demand and supply overvaluation signals. Notably, this housing boom signal appeared before the exuberance indicators employing MEB tests on house price fundamentals provided overvaluation evidence (Coulter et al., 2022).

Figure 2: Housing booms fueled by credit.



Notes: Probabilities of being in each state using Model 2 results. DCFM means dynamic common factor model, which provides house prices overvaluation signals plotted in gray (see Appendix F for a description). MEB tests are the mildly explosive behavior tests as reported by Shi (2017) and the Dallas Fed (see https://www.dallasfed.org/research/international/houseprice#tab2).

4 Countercyclical macroprudential policy

One of the critical challenges faced by central banks is the management of credit-driven booms and busts, characterized by alternating periods of exuberant credit expansion and abrupt contractions, often leading to systemic risks and economic vulnerabilities. Motivated by the desirability of asymmetric macroprudential policy (Gatt, 2023, Cerutti et al., 2017a), this section proposes a state-dependent macroprudential policy rule that exploits the previously defined nonlinear model of housing booms fueled by credit, which is expressed as follows:

$$Y_t = \phi_1 \cdot Y_{t-1} + \phi_2 \cdot \left[\sum_{i=1}^{4} P(S_t = i)_t \cdot c_i \right] \tag{12}$$

where Y is the level of a particular policy tool chosen at time t, ϕ_1 and ϕ_2 are smoothing parameters that sum up to one, $P(S_t = i)_t$ are the probabilities of being in states $S_t = [1,2,3,4]$ as estimated in each month t by the Markov switching Model 2 shown in previous sections[10]. Notably, the coefficients c_i where $i = [1,2,3,4]$ are the policy tool target levels chosen depending on the housing market state[11]. While coefficients c_i must be chosen for each policy tool and state, the smoothing parameters ϕ_1 and ϕ_2 are assumed to be always set equal to 0.9 and 0.1, respectively.

The motivation for using equation (12) is as follows. First, policymakers need to know the state of the credit and housing markets as a precondition for implementing a countercyclical policy aimed at taming credit-driven booms and busts. This is informed by the state probabilities $P(S_t = i)_t$ estimated using the Markov switching model. Second, after choosing a certain policy tool Y, an active policymaker must decide which policy levels to impose in each state, corresponding to the parameters c_i. Importantly, these parameters must be selected such that they are countercyclical. Third, the smoothing parameters ϕ_1 and ϕ_2 govern the speed at which the policy level in t adjusts from the level chosen in $t-1$, thus allowing the policymaker to determine the smoothness of the desired policy tool. Fourth, Equation (12) is general, such that one can use a different model to inform the state of the economy, and it can also be used to estimate the levels of diverse macroprudential policy tools, as shown below.

To show how to set a countercyclical macroprudential policy using equation (12), I apply this policy rule to set three hypothetical tools: a sectoral countercyclical capital buffer, a mortgage interest deduction, and a dividend payout restriction. Although these tools are available to policymakers, they appear relatively underused in most jurisdictions, including the US, despite their potential to deal with real estate booms (Crowe et al., 2013). First, the sectoral countercyclical capital buffer (SCCyB) was proposed by the BIS (2019a, 2019b), which is a variation of the traditional countercyclical capital buffer and is an additional capital requirement for banks during periods of excessive credit growth concentrated within specific sectors, such as real estate, construction, or consumer credit. Furthermore, the literature shows that higher capital requirements for banks are an effective way to increase the resilience of the banking sector and contain both credit and housing prices (see Ampudia et al., 2021 and Mendicino et al., 2020, among others). Using a sectoral

[10] Therefore, Y_t is conditional on the information that feed the Markov switching Model 2, that is: S&P Case-Shiller home price index, measures of employment (*all employees: total non-farm payrolls*), wages (*gross domestic income: compensation of employees, paid: wages and salaries*), housing rental prices (*CPI for urban consumers: rent of primary residence*), and mortgage debt (*mortgage debt outstanding, individuals, and other holders*).

[11] The state-dependent policy target levels for each policy tool discussed in this section were chosen for expositional purposes. In a more realistic exercise, they may be calibrated and/or time-varying.

version of the tool such that the focus is on risks associated with the housing sector seems to be a natural choice for this application.

The second policy tool considered in this application is the mortgage interest rate deduction (MID) at the disposal of governments. This tax provision allows individuals who own a home and have a mortgage to deduct a portion of the interest they pay on their mortgage loan from their taxable income. In many countries, including the US, this deduction is typically provided as an incentive to promote homeownership at the cost of stimulating the housing market. Over the last two decades, several studies have discussed the effects of this tool since Gervais (2002). Despite the disagreement in the literature with respect to the short-run costs of a transition to deduction removal, there appears to be consensus on the long-run welfare gains associated with the elimination of this deduction (see Karlman et al., 2021). Moreover, given that this deduction has a direct impact on government revenue, a countercyclical approach to this tool could help governments obtain a fiscal space that might be useful during implosion times to support financial stability. Thus, this policy might allow governments to incorporate financial stability considerations into the design of fiscal policy, as advocated by Borio et al. (2023), while disincentivizing the accumulation of mortgage debt by households during housing booms fueled by credit. Recent theoretical work by Arce et al. (2023) suggests that an optimal tax on borrowing is always desirable macroprudential policy.

In this application, the third policy tool is dividend payout restrictions on banks (DPR). This refers to the imposition of a cap on the maximum dividend banks can deliver to their shareholders, which is a tool for the disposal of central bankers. The rationale for this instrument is that banks could jeopardize their capitalization if they provide sizable dividends during bad times, which might subsequently affect their capacity to provide credit and, if necessary, absorb losses. As noted in Stein (2021), a payout curtail during the Great Recession could have attenuated the impact of the ongoing banking crisis on the real economy. Furthermore, Acharya et al. (2017) show in their theoretical framework that the interconnections between banks' capital policies can generate strong externalities, leading to excessive dividends and inefficient capitalization. Along these lines, dividend restrictions were introduced in the US during the Covid-19 crisis, as in many other jurisdictions (see Hardy, 2021). Theoretical work by Muñoz (2021) shows that this tool is effective in smoothing the financial cycle and generates significant welfare gains with respect to traditional capital regulation. In addition, Dautovic et al. (2023) show that the DPR imposed in the Euro area during the pandemic was effective in limiting pro-cyclicality while adding capital space to banks.

To compute the levels of each of the three hypothetical policy tools for each period from Equation (12), I specify the parameters c_i as described in Table 5. The general reasoning behind this parameterization is to choose an expansionary coefficient c_4 to ease credit conditions during busts, instead fixing contractionary parameters c_2 and c_3 during housing booms fueled by credit and considering an intermediate value c_1 during the state 1 times, such that the particular tool is countercyclical. Regarding the SCCyB, I fix the parameters such that $c_1 = 1\%$ (i.e. a positive cycle-neutral SCCyB), $c_2 = 2.5\%$, $c_3 = 4\%$ and $c_4 = 0\%$ in percent of sectoral risk weighted assets (RWA), thus 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%. Thus, the banking system is expected to react by limiting households' credit growth during housing booms and easing access to credit during implosion. Instead, the parameterization of the MID is set such that in state 1, households can deduct half of their mortgage debt service costs (c_1 = 50%); however, during the booming state 2 only half of that deduction is possible (c_2 = 25%), and no deduction is possible during the most exuberant housing booms (c_3 = 0%), while households can deduct all their mortgage debt costs during busts (c_4 = 100%). Therefore, potential homeowners are disincentivised to take a mortgage during booms, while they receive a tax incentive to get one during busts. Finally, regarding DPR, the employed parameterization assumes that banks can redistribute 25% of their net earnings during normal times (c_1 = 25%), which is around the actual average after the Great Recession. Instead, they are allowed to distribute up to half of their net earnings during housing booms (c_2 = 37.5%; c_3 = 50%). By contrast, they could not pay any dividend during implosion times (c_4 = 0%), which would guarantee the protection of their capital when competition and signaling might encourage them to pay a risky dividend.

Table 5: Parameterization of the policy tools levels, by state.

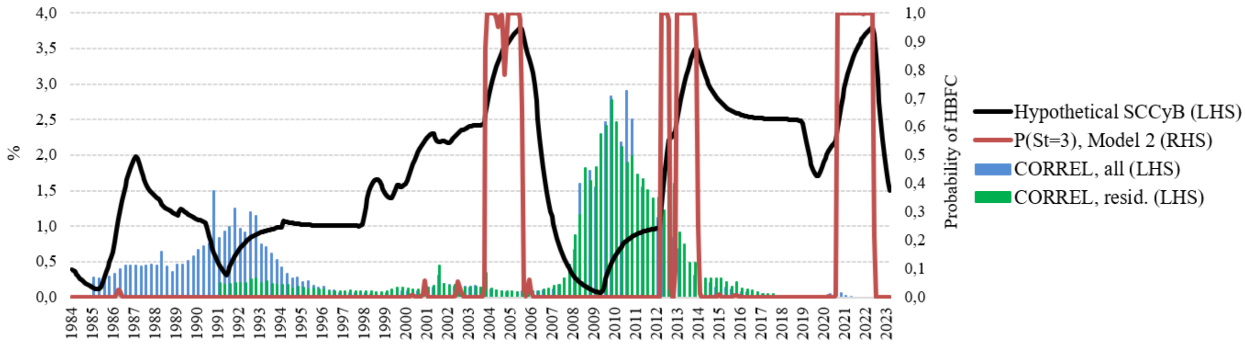
Policy tools	**Parameters**			
	c_1	c_2	c_3	c_4
Model 2 (four states)				
Sectoral CCyB (SCCyB)	1%	2.5%	4%	0%
Mortgage interest rate deduction (MID)	50%	25%	0%	100%
Dividend payout restriction (DPR)	25%	37.5%	50%	0%

Notes: Parameters c_1, c_2, c_3, and c_4 correspond to the chosen policy tools levels during state 1, 2, 3, and 4, respectively, for a four-state Markov switching model (Model 2, see Section 2).

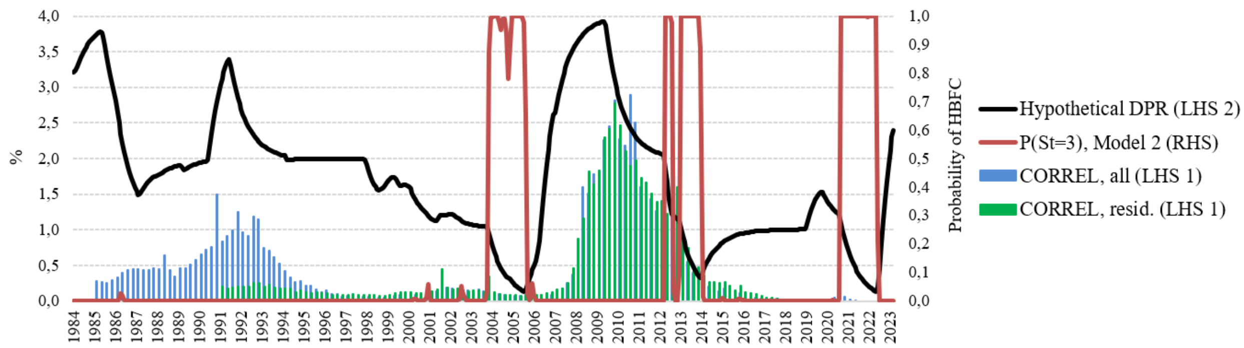
Figure 3 plots the levels of the hypothetical macroprudential policies (black solid lines) examined in this section, together with the charge-off rates of real estate loans (”all loans” in blue bars, ”residential loans” in green bars) and the probability of being in a housing boom fueled by credit as represented by state 3 probabilities (red solid line) estimated by the Markov switching Model 2 described in previous sections. The charge-off rate of real estate loans is the percentage of banks' debt outstanding that is delinquent or bad debt. Several observations emerge. First, the patterns of the three policy tools are the same or inverted because they are fed by the same probabilities of being in each of the four states provided by the Markov switching model. Second, during the housing boom fueled by credit in the 2000s, the three policy tool levels jumped smoothly towards the chosen contractionary c_3. As it turns out, periods of high charge-off rates on real estate loans (i.e., during the early 90s and the late 2000s) are preceded by years in which the policy rules prescribe contractionary levels, suggesting leading and countercyclical behavior for such hypothetical policy tools. Furthermore, during the Great Recession, when the charge-off rates of real estate loans reached a maximum, the policy levels hit expansionary c_4, consistent with the countercyclical reasoning of the selected parameterization.

Figure 3: Hypothetical countercyclical macroprudential policies.

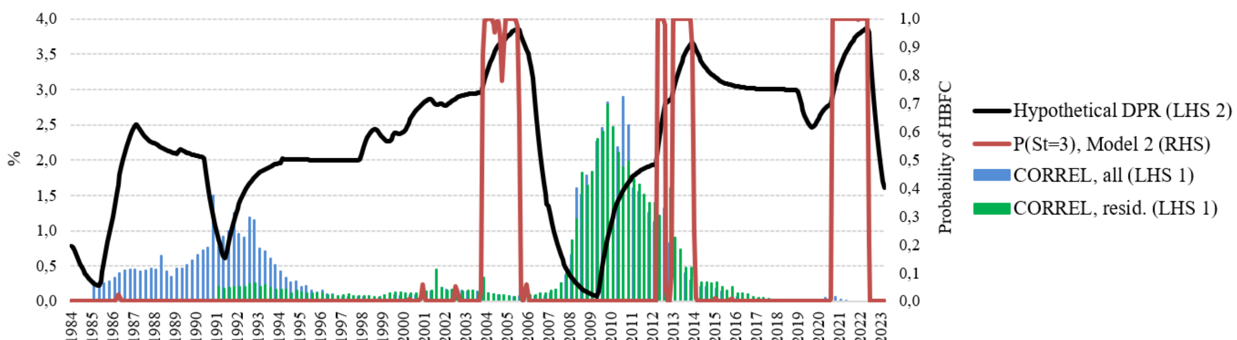
A) Sectoral countercyclical capital buffer (SCCyB).



B) Mortgage interest deduction (MID).



C) Dividend payout restrictions (DPR).



Sources: Own calculations and Board of Governors of the Federal Reserve System data.
Notes: CORREL refers to charge-off rates of real estate loans. Charge-off rates on real estate residential loans is only available from February 1992. In subfigure A, the left hand side scale represents the percent with respect to sectoral RWA (hypothetical SCCyB) or to total loans (CORREL). In subfigure B, the left hand side has 2 scales. LHS 1 (left) reflects the percent of charge-off rates on loans with respect to the total loans of the banking system (CORREL), while the LHS 2 (right) represents the percent of the interest rate paid by borrowers that is deductible (hypothetical MID). In subfigure C, the left hand side scale has 2 scales. LHS 1 (left) reflects the percent of charge-off rates on loans with respect to the total loans of the banking system (CORREL), while the LHS 2 (right) represents the percent of the dividend payout restriction (hypothetical DPR).

5 Assessment of early warning signaling content

In this section, I delve into an assessment of the early warning content of the hypothetical policy tools described in the previous section, which in turn builds on the probabilities of being in normal times, housing booms fueled by credit, and implosion times, as computed using a Markov switching model. The reasoning behind this exercise is that if those probabilities capture the risks of housing booms and busts, and if the parameterization of the policy rules is countercyclical, such hypothetical policy rules should provide predictive value in forecasting materialized risks in housing finance. This is similar in spirit to Greenwood et al. (2022), who find that their red zone indicators have predictive power for financial crises in a large set of countries.

While the ultimate materialization of macro-financial risk is arguably a financial crisis, a natural leading indicator of housing finance risk is the variable charge-off rate of real estate residential loans, namely, the share of bad housing loans in banks' portfolios. An additional risk indicator considered in this section is the St. Louis Fed Financial Stress Index, which measures the degree of financial stress in the markets and builds mostly on interest rate series and yield spreads. In particular, I implement a forecasting exercise to examine whether the computed hypothetical policy tools contain useful information to predict such risk measures, which would suggest that they are useful in providing early warning signals of real estate booms and financial risks, which, in turn, might suggest that they might be timely in policy-making.

Despite the importance of the riskiness of loan portfolios in the banking system for financial stability, only a few studies tackle the problem of modeling and forecasting the charge-off rate of banking loans, and there is no consensus on which approach to employ[12]. Thus, given the presence of modeling uncertainty, a natural approach is to use agnostic models, such as factor models, which allow for dimensionality reduction and to feed them with a large set of macroeconomic predictors. In this exercise, I follow the approach of Kim and Son (2023) and use a factor-augmented vector autoregression (FAVAR) model and a wide US macro dataset, such as the FRED-MD, as a benchmark forecasting model. As these authors show, this type of model outperforms alternative models in predicting the charge of rates of real estate loans.

The forecasting exercise performed in this section is as follows. First, I summarize the monthly FRED-MD dataset, which includes 127 macro and financial US variables based on seven factors, as determined by using the test of Bai and Ng (2002). As previously mentioned, the target variables to forecast are the charge-off rate of real estate residential loans (CORREL), for which the data series starts in February 1992, and the St. Louis Fed Financial Stress Index (STLFSI4), which starts in January 1994. Second, I consider three augmented models, which consist of the benchmark FAVAR model plus one additional policy tool at a time, that is, the hypothetical SCCyB, MID, and DPR, as shown in the previous section. I also report the performance of a naïve model, that is, an autoregressive AR(12) model, including 12 lags. Finally, I evaluate the forecasting performance of the five models up to 12 months ahead considering the subsample January 2007 - February 2020 as the evaluation sample, to avoid distortions coming from the policies implemented to contain the effects of the Covid-19 pandemic. Table 6 reports the relative root mean squared errors (RMSE)

[12] Kim and Son (2023) show that factor models perform well in predicting the charge-off rates of business and real estate loans using a large panel of macro indicators. Barth et al. (2020) find that Ridge regressions, elastic nets and factor models provide accurate forecasts of charge-off rates for four US banks. Sheng et al. (2022) employ a panel Tobit model to assess the importance of uncertainty in forecasting charge-off rates of small US commercial banks.

of the five forecasting models considered with respect to the FAVAR benchmark. As it turns out, the inclusion of hypothetical policy tools increases the forecasting performance of the benchmark FAVAR model to predict CORREL up to 17%, and up to 4% to forecast STLFSI4. These results suggest that despite using a competitive model as a benchmark, the policy tools additionally contain useful information to predict housing finance and financial stress risks, meaning that if implemented, these tools might lead the materialization of risks in the banking sector coming from housing loans and financial stress risks.

Table 6: Forecasting performance of the hypothetical tools: Relative RMSE vs FAVAR model.

Target	**CORREL**	**STLFSI4**
Benchmarks		
FAVAR	1.00	1.00
AR (12)	1.05	1.16
Augmented models		
FAVAR with SCCyB	0.93	0.97
FAVAR with MID	0.83	0.96
FAVAR with DPR	0.83	0.96

Notes: Relative RMSE is the ratio of the RMSE of each considered model with respect to the benchmark FAVAR model, which is a monthly FAVAR model with 7 factors summarizing the FRED-MD dataset, Minnesota priors and 11 lags. The AR(12) model is an autorregressive model of order 12. CORREL are the charge-off rates on residential real estate loans of the banking sector. STLFSI4 is the St. Louis Fed Financial Stress Index.

6 Discussion

The outcomes of this research provide insights into a new model to identify the state of the housing market, focusing on catching housing booms fueled by credit and how to exploit it in a state-dependent policy rule. Moreover, I show that this procedure can produce policy tools or indicators that provide early warning signaling content to predict proxies for financial risk. In this section, I discuss the differences of the proposed approach with respect to other ones, some policy implications, as well as some of the limitations of this study.

Compared with other approaches to monitoring the housing market, the approach proposed in this study offers the following advantages. First, in contrast to empirical studies targeting the identification of housing bubbles, such as mildly explosive behavior tests, this study builds a regime-switching model to identify housing booms fueled by credit. I believe that this crucial phenomenon deserves a tailored modeling approach, despite the importance of bubbles, which are slightly different events. Notably, monitoring housing booms fueled by credit might give macroprudential policymakers a stronger narrative for setting housing policies. Second, compared to the household red-zone of Greenwood et al. (2022), the approach taken in this study allows data to speak without imposing specific thresholds to determine risky levels, which might be somewhat ad-hoc and country-dependent. Notwithstanding, a suite-of-models approach to monitoring the housing market welcomes the input from all these complementary approaches.

Some policy implications emerge from this study's empirical results. First, during the 2000s housing boom, Markov switching Model 2 started providing booming signals from 1999 (states 2 and 3), which in retrospect might have been useful to policymakers in driving policy tools that, according to the state-dependent policy tools shown in this study, would have been increasingly tight from 1999 to 2006. Second, after the pandemic hit in March 2020, the model continued to provide booming signals that were especially strong from September 2020 to May 2022, thus prescribing policy-tightening. Therefore, according to these results, the easing of policies prevalent at that time might have been unnecessary, at least with regard to the housing market. Nevertheless, it must be noted that these considerations are formulated with the benefit of hindsight.

Regarding the limitations of this study, those related to the Markov switching model are as follows. First, this model does not provide an estimate of the size of overvaluation or undervaluation of house prices, as it is not the target of this study. Second, given the lack of data on foreign housing demand, which is common to most (if not all) economies, such measures were not included in the models. Regarding the proposed state-dependent and countercyclical policy rules, the following caveats emerge. First, the chosen target policy levels are time-invariant and hypothetical. Interested policymakers may prefer to calibrate such targets. Second, the same applies to smoothing parameters, which might be time-varying, such that they require a higher or lower speed of adjustment depending on additional data or the policymaker's judgment.

7 Concluding remarks

Empirical evidence related to excessive leverage, housing price growth, and financial instability has been accumulated since the Global Financial Crisis. As a result, new banking regulations have emerged to reduce the likelihood of housing booms causing macroeconomic damage. The theory suggests that policymakers might succeed in doing so; however, they need at least two ingredients for an effective recipe. First, they must know the housing market state at each point in time. Second, they require a state-contingent policy rule to implement an appropriate countercyclical policy on a timely basis. To date, there has been no consensus among researchers and policymakers regarding how to address both issues.

In this paper, I address such questions using a regime-switching approach. First, I use a Markov switching model to estimate the probability of being in different housing states. Second, I exploit such probabilities to feed a state-contingent policy rule, which I apply to setting a hypothetical housing countercyclical capital buffer (SCCyB), mortgage interest deduction, and dividend payout restriction. Finally, I show that such tools contain early warning information, as they improve the forecasting accuracy of a benchmark model in predicting charge-off rates for real estate residential loans and the St. Louis Fed Financial Stress Index. These results suggest that the three-step approach employed in this study might be useful for housing analysts and policymakers to monitor the housing market and implement state-dependent macroprudential policies in a timely manner.

Future research along these lines may proceed in the following directions. First, it is necessary to perform an impact analysis of the hypothetical macroprudential policies proposed in this study, which may require the use of a non-linear general equilibrium model. Second, the policy rule employed in this study may also be used to drive other policy tools. Finally, the work done in this study may be replicated with data from other countries and also US state-level data.

Appendices

A Data

Table 7: Time series data.

Variable	Acronym	Source	Data transformation
S&P Case-Shiller home price index	HP	S&P	R, L, D
Compensation of employees	W	BEA	R, L, D
Employees, non-farm payrolls	E	BLS	L, D
Urban primary residence rent index	R	BLS	R, L, D
Mortgage debt outstanding, all holders	D	BG	SA, M, R, D
Working age population: aged 15-64	-	OECD	L, D
30 year fixed rate mortgage average	-	FM	-
Fed funds	-	BSL	-
Real estate loans owned and securitized	-	BG	R
Industrial production	-	BG	L
Real manufacturing and trade sales	-	BSL	L
Housing starts	-	CB	L
New private housing building permits	-	CB	L
New one family houses sold	-	CB	L
Supply of new houses	-	CB	L
New private homes under construction	-	CB	L
Industrial production: Cement	-	BG	L, R
Charge-off rate on loans secured by real estate: all loans	CORREL, all	BG	M
Charge-off rate on loans secured by real estate: residential loans	CORREL, resid.	BG	M
St. Louis Fed financial stress index	STLFSI4	BSL	-

Notes: In the last column, *L* means logs, *D* means taking one difference, *R* means that the variable has been transformed into real terms by applying the CPI, and *M* means that the series has 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, and BSL means Federal Reserve Bank of St. Louis, OECD stands for the Organization for Economic Cooperation and Development, and FM means Freddie Mac. FHFA stands for Federal Housing Finance Agency.

B Markov switching models: estimation

For simplicity, let us assume a two-state Markov switching model such that states s_t can be equal to 1 or 2. Let θ be the vector of parameters entering the likelihood function for the data, and assume that the density conditional on being in state $j, \eta(HP_t \mid s_t = j, X_t, Y_t; \theta)$ is Gaussian:

$$\eta(HP_t \mid \Omega_t, s_t = j; \theta) = \frac{1}{\sqrt{2\pi h_j}} \exp\left(\frac{-(HP_t - \beta_{0,s_t} - \beta_1' X_t - \beta_{2,s_t}' Y_t)^2}{2h_j}\right) \tag{13}$$

for j = 1,2. The information set Ω_t contains HP_t, X_t, Y_t, ω_t and the lagged values of these variables, such that $\Omega_t = \{HP_t, X_t, Y_t, \omega_t, \Omega_{t-1}\}$.

Note 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 conditioning factors X_t and house prices is constant.

The log-likelihood function takes the following form:

$$\ell(HP_t \mid \Omega_t; \theta) = \sum_{t=1}^{T} \ln(\phi(HP_t \mid \Omega_t; \theta)) \tag{14}$$

where the density $\phi(HP_t \mid \Omega_t; \theta)$ is obtained by summing the weighted probability state densities across the two possible states such that:

$$\phi(HP_t \mid \Omega_t; \theta) = \sum_{j=1}^{2} \eta(HP_t \mid \Omega_t, s_t = j; \theta) P(s_t = j \mid \Omega_t; \theta) \tag{15}$$

where $P(s_t = j \mid \Omega_t; \theta)$ is the conditional probability of being in state j at time t given the information set Ω_t.

The conditional state probabilities can be obtained recursively such that:

$$P(s_t = i \mid \Omega_t; \theta) = \sum_{j=1}^{2} P(s_t = i \mid s_{t-1} = j, \Omega_t; \theta) P(s_{t-1} = j \mid \Omega_t; \theta) \tag{16}$$

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

$$\begin{aligned} & P(s_{t-1} = j \mid \Omega_{t-1}; \theta) = P(s_{t-1} = j \mid HP_{t-1}, X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2}; \theta) \\ = & \frac{\eta(HP_{t-1} \mid s_{t-1} = j, X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2}; \theta) P(s_{t-1} = j \mid X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2}; \theta)}{\sum_{j=1}^{2} \eta(HP_{t-1} \mid s_{t-1} = j, X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2}; \theta) P(s_{t-1} = j \mid X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2}; \theta)} \end{aligned} \tag{17}$$

C Markov switching models: Additional estimates

Table 1 (cont.): Markov switching model estimates.

	Model 1		Model 2	
Time-varying transition probabilities				
p(1,1), constant	1.911***	(0.31)	1.804***	(0.26)
p(1,1), mortgage debt (D)	36.549*	(18.99)	-0.325	(24.35)
p(1,2), constant	-2.232**	(0.98)	-5.427	(60977)
p(1,2), mortgage debt (D)	-47.661	(172.5)	5.021	(56074)
p(1,3), constant	-1.648***	(0.34)	-2.120***	(0.76)
p(1,3), mortgage debt (D)	-21.129	(20.63)	5.330	(38.47)
p(1,4), constant	-	-	-1.797***	(0.39)
p(1,4), mortgage debt (D)	-	-	5.592	(28.32)
p(2,1), constant	6.702	(199.10)	11.052	(50053)
p(2,1), mortgage debt (D)	2457.02	(74936.2)	2457.86	(81786)
p(2,2), constant	1.843***	(0.52)	4.329	(10849)
p(2,2), mortgage debt (D)	-9.045	(38.74)	-0.032	(85828)
p(2,3), constant	-2.503	(2.95)	-4.564	(13152)
p(2,3), mortgage debt (D)	-49.035	(218.30)	0.001	(14925)
p(2,4), constant	-	-	-0.191	(1.33)
p(2,4), mortgage debt (D)	-	-	23.038	(83.22)
p(3,1), constant	-	-	11.005	(40063)
p(3,1), mortgage debt (D)	-	-	2457.0	(75847)
p(3,2), constant	-	-	-1.486***	(0.35)
p(3,2), mortgage debt (D)	-	-	-2.588	(22.85)
p(3,3), constant	-	-	1.542***	(0.42)
p(3,3), mortgage debt (D)	-	-	21.774	(26.38)
p(3,4), constant	-	-	-3.889	(17908)
p(3,4), mortgage debt (D)	-	-	0.048	(14117)

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. The time-varying transition probabilities are denoted p(i,j), means probability of transition from state i to state j.

D Markov switching models: Statistical tests

Table 8: Statistical tests.

	Model 1	**Model 2**
Number of states	3	4
Unrestricted log likelihood value	1705.78	1798.16
A) Tests for number of states		
Log likelihood value with		
maximum number of states $s = 2$	1535.93	-
p-value	0.00	-
Log likelihood value with		
maximum number of states $s = 3$	-	1705.78
p-value	-	0.00
B) Tests for identical mean parameters		
Log likelihood value with		
$\beta_{0,s_t=1} = \beta_{0,s_t=2} = \beta_{0,s_t=3}$	1639.26	-
p-value	0.00	-
Log likelihood value with		
$\beta_{0,s_t=1} = \beta_{0,s_t=2} = \beta_{0,s_t=3} = \beta_{0,s_t=4}$	-	1378.28
p-value	-	0.00
Log likelihood value with		
$\beta_{4,s_t=1} = \beta_{4,s_t=2} = \beta_{4,s_t=3}$	1678.56	-
p-value	0.01	-
Log likelihood value with		
$\beta_{4,s_t=1} = \beta_{4,s_t=2} = \beta_{4,s_t=3} = \beta_{4,s_t=4}$	-	1695.42
p-value	-	0.00
C) Tests for identical variance parameters		
Log likelihood value with		
$\lambda_{0,s_t=1} = \lambda_{0,s_t=2} = \lambda_{0,s_t=3}$	1644.97	-
p-value	0.00	-
Log likelihood value with		
$\lambda_{0,s_t=1} = \lambda_{0,s_t=2} = \lambda_{0,s_t=3} = \lambda_{0,s_t=4}$	-	1769.15
p-value	-	0.01
D) Tests for identical probability parameters		
Log likelihood value with		
$\pi_{1,p} = \pi_{1,q} = \pi_{1,z}$	1535.70	-
p-value	0.00	-
Log likelihood value with		
$\pi_{1,p} = \pi_{1,q} = \pi_{1,z} = \pi_{1,r}$	-	1689.96
p-value	-	0.00
E) Tests of heteroskedasticity		
Goldfeld-Quandt test on mortgage debt (D)		
F-statistic	0.29	0.31
Critical value	1.26	1.27

Notes: See Section 3 for a description of models 1 and 2. The Goldfeld-Quandt test orders the resulting residuals of each model by the variable mortgage debt (D), and divides the full sample in two, omitting six central observations. Then, it tests the null hypothesis of homoskedasticity.

E Markov switching Model 1 results

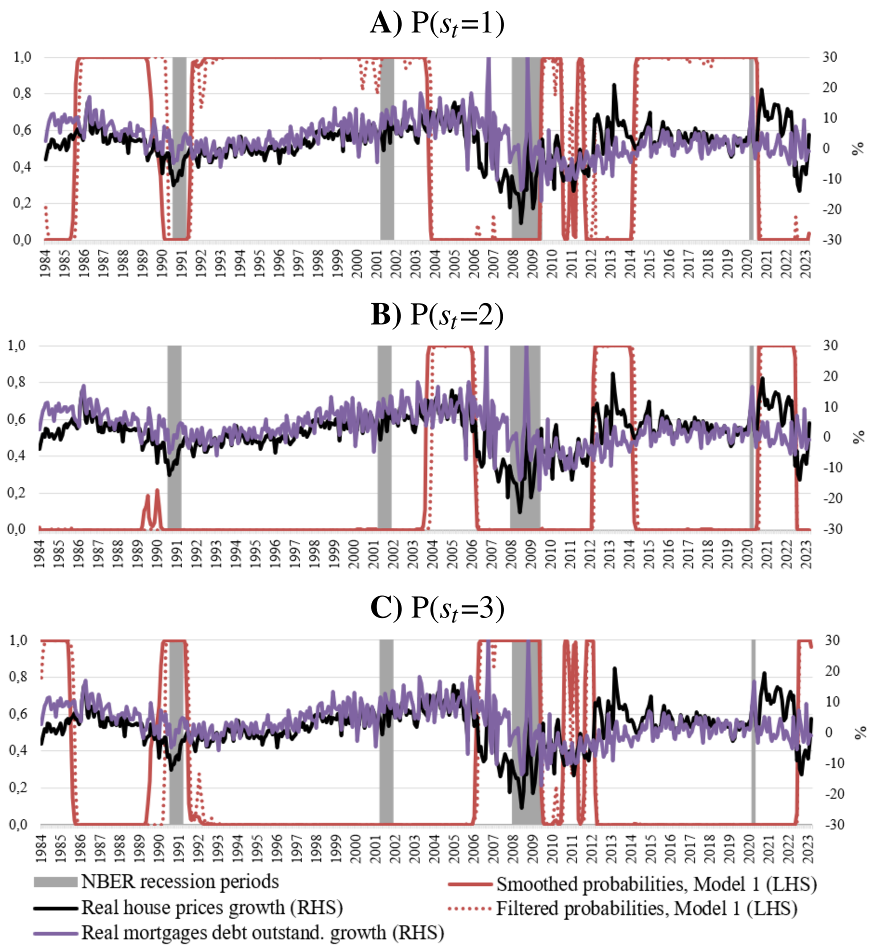
Table 9 shows the latest transition probabilities for Markov switching Model 1.

Table 9: Latest transition probabilities matrix, Model 1.

		State in T-1		
		1	2	3
	1	0.96	0.02	0.06
State in T	2	0.00	0.95	0.01
	3	0.04	0.03	0.93

Figure 4 shows a comparison of the filtered (red line) and smoothed (blue line) Markov switching probabilities of each of the three states according to Model 1.

Figure 4: Markov switching probabilities of being in state S_t, Model 1.



F Factor models of housing demand and supply

The structure of the dynamic factor models is common for both demand and supply specifications. I first assume that housing demand and supply are better proxied by several indicators than taking one of them. Second, I assume that the fundamentals included in each of the models are reasonable proxies, as is commonly used in the literature. Third, using the common factor implies that co-movements between 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 form. The dynamic common factor model of housing demand (or supply) yields:

$$y_t = \gamma c_t + e_t \tag{18}$$

where c_t is the common factor that follows an autoregressive structure of order two, such that:

$$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + w_t \tag{19}$$

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

$$e_{i,t} = \psi_{i,1} e_{i,t-1} + \psi_{i,2} e_{i,t-2} + \varepsilon_{i,t} \tag{20}$$

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

The selected housing demand fundamentals in log-differences are the 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[13]. Alternatively, the factor model of housing supply includes three variables in logs: new one-family houses sold, building permits, and housing starts, which are commonly used in the literature to track housing supply development (see Hilbers et al., 2008).

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

$$O_t = HP_t - f_t \tag{21}$$

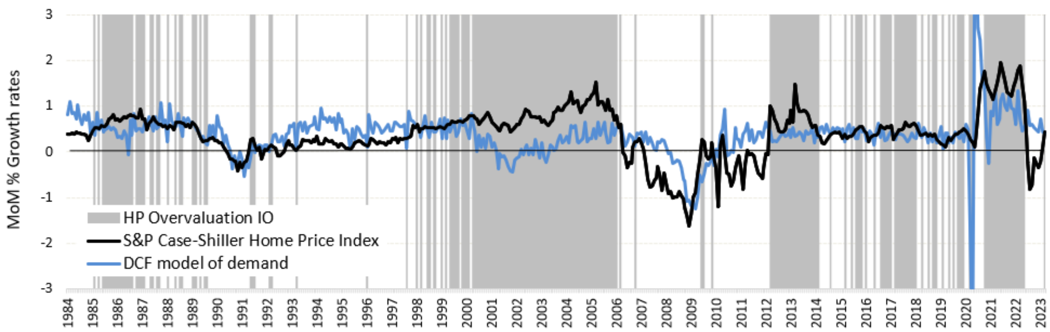
Finally, this time series of overvaluation O_t is used to generate a binary indicator of overvaluation IO_t such that:

$$IO_t(O_t) = \begin{cases} 1 & \text{if } O_t > 0 \text{ and } HP_t > 0 \\ 0 & \text{otherwise} \end{cases} \tag{22}$$

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

Figure 5 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 70 months from April 2000 to January 2006, that is, the years before the Great Recession. Other periods of overvaluation were August 1985 to August 1986, March 2012 to October 2013, August 2016 to January 2018, and discontinued in February 2017.

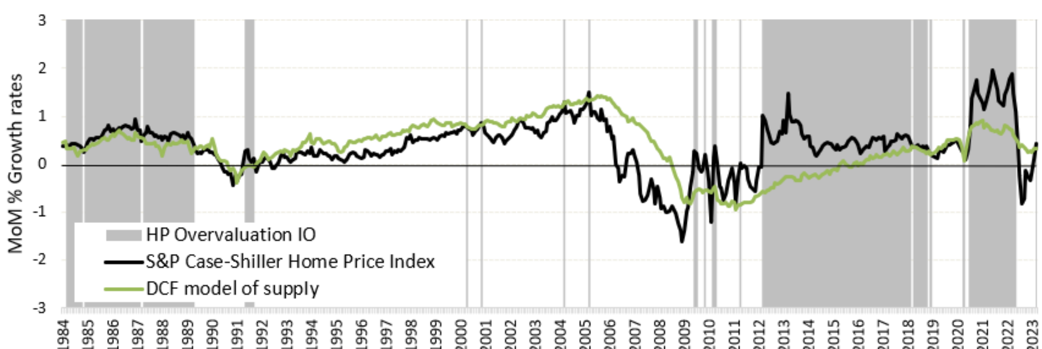
Figure 5: Common factor of housing demand and house prices.



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 housing prices is 34.3%.

Figure 6 shows the dynamic common factor of the housing supply (green line). According to this setup, there were two periods of overvaluation, from January 1984 to April 1989 and from March 2012 to December 2018, both with some monthly discontinuities.

Figure 6: Common factor of housing supply and house prices.



Notes: The housing supply proxies included are *new one-family houses sold*, *building permits*, and *housing starts*. The correlation between the supply factor and house prices is 53.9%.

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