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Jan Prüser and Torsten Schmidt[1]

Regional Composition of National House Price Cycles in the US

Abstract

House price cycles may have considerable macroeconomic effects even if they evolve heterogeneous across local markets. In this paper we use a panel Markov switching model allowing for time-varying volatility to analyze national and state level house price regimes for the US jointly. Our approach identifies three house price regimes endogenously. A nationwide boom regime, a spatially limited bust regime and a nationwide bust regime. The spatially limited bust regime occurs in the coastal states where compared to other states the population density is high, the unemployment rate, the housing density as well as the land supply elasticity is low. This spatially limited bust regime usually follows a nationwide house price boom. Hence, house price movements in the coastal states usually determine the nationwide cycle in the US. Moreover, boom and bust cycles are accompanied by an exaggeration of house price increases during the boom in this group of states. In contrast, a bubble in the housing market occored in almost all states previous to the Great Recession. This is one explanation for the severity of the Great Recession.

JEL-Code: E31, R31, C11, C32

Keywords: House price cycles; regional house prices; markov switching

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1. Introduction

The recent financial crisis has shown dramatically how important it is to detect national boom and bust cycles in housing markets at an early stage. However, in housing markets it is more difficult to detect exaggerations in price developments than in other property markets. The reason is that housing markets are highly segmented and house price developments are heterogeneous across market segments. In this market structure the challenge is to detect price developments that endanger economic developments or the stability of the financial sector of the whole economy. Therefore, as in any other property market it is necessary to decide whether an increase in prices is a speculative bubble or driven by fundamentals. Furthermore, it is necessary to decide with regard to the whole economy whether a critical number of housing units is affected by the price increase. For this reason it is informative to analyze nationwide house price cycles with regional data.

Common approaches to detect house prices cycles follow the business cycle literature by identifying peaks and troughs in an aggregated house price index (Igan and Loungani, 2012) and (Sinai, 2012) or by using a Markov switching model Chen et al. (2014). However, these approaches focus on the level of house prices or their changes. They neglect information about the regional distribution of house price increase. On the other extreme using local house price data incorporates a lot of noise due to idiosyncratic local market conditions. To distinguish a national housing cycle from idiosyncratic components Negro and Otrok (2007) use a factor model. Based on this decomposition they find, that house price movements have mainly been driven by the idiosyncratic component. However, the fact that house price cycles are not synchronized between all local entities does not mean that they are totally independent. As it is often the case we argue in this paper that the truth lies in between. For this reason we use state level data to analyze house price cycles in the US. Our approach allows us to distinguish national house price cycles and cycles that are confined to a limited number of states endogenously.

Empirical studies of house prices at the state level typically find that house price dynamics can be distinguished between two groups of states. For instance Rapach and Strauss (2009) test the forecast ability of house prices across US states. The most significant differences occur between interior and coastal states. More specifically, they find for the period 1995 to 2006 that house price forecasts based on economic fundamentals perform relatively well for interior states and relatively poor for coastal states where house price increases were especially strong during this period. This grouping of states is also found in a study of Fratantoni and Schuh (2003). They analyze the effects of monetary policy shocks on regional housing markets and find that coastal states experienced a housing boom in the late eighties while the interior states do not. Moreover, their results show that monetary policy is moderately less effective during this period. These findings indicate that it is sufficient that house price cycles takes place in some states, mainly the coastal states to have a national impact.

In this paper we analyze a panel of house prices at the state level to characterize nationwide and regional house price cycles. Using a panel data set with large cross-section and time series dimensions raises two separate questions. The first is which states share the same comovement and the second is how the house price cycle itself is defined. In order to address these two questions we use the econometric framework of Hamilton and Owyang (2012). This model was recently used to analyze the relationship between house price dynamics and the business cycle (Hernandez-Murillo et al., 2017). The model is attractive for our purpose for several reasons. First, in contrast to existing studies it endogenously assigns the states to different clusters. States in the same cluster share a similar house price dynamic and therefore allows us to investigate which regions are characterized by the same house price cycle. Second, it models the probability of a state's belonging to a cluster as a logistic variable, in which the state characteristics affect the prior probability of a state membership on a regional cluster. This allows us to investigate, which characteristics states have in common and which share a regional house price cycle. Finally, the model estimates the regional house price cycles by assuming that a Markov switching process determines which clusters are in a boom or recession. Thus, the model endogenously defines house price cycles. This allows us distinguish nationwide and regional house price busts.

Within this framework a house price boom is not simply a strong increase in the nationwide house price index. Rather, a nationwide house price boom occurs when house prices increase in almost all states and a national bust occurs when house prices decline in almost all states. Moreover, this model allows for additional regimes. Our results reveal that an important third regime is designated to spatially limited busts. This third regime is characterized by a cluster of states with high population density, low unemployment rate, low housing density and lw land supply elasticity. An important hypothesis of this paper is, that this combination of restricted housing supply and high demand is an important factor of a pronounced house price cycles because it favors the onset of exaggerations of price increases.

It is shown that before the Great Recession nationwide house price cycles in particular house price busts are mainly take place in certain states. Pronounced cycles in house prices are mainly visible in the east coast states like New York, Rhode Island and New Jersey as well as in California. These states form a cluster that is captured by the spatially limited bust regime. In these states strong increases are followed by pronounced drops in house prices. In all other states the increases in house prices are not as pronounced as in the former group. And more importantly house price indices are not falling before the Great Recession.

In contrast, the Great Recession was the only period in our sample where house prices in all states dropped considerably after the occurence of a bubble in house prices. This highlights the uniqueness of this period. Normally, states with a lower population density have a stabilizing effect on the overall house price cycles. In contrast, the model is not able to detect differences in the speed of price increases.

The outline of the paper is as follows: In Section two we present some regularities about regional house price cycles. In particular, we highlight the differences and similarities in regional cycles. In the following Section we present our model and the estimation strategy and in Section four our results. Finally, we draw some conclusions in Section five.

2. Similarities and differences of house price dynamics at the state level

To identify nationwide cycles in house prices we start by describing house price cycles at the aggregate level based on data from the Federal Housing Finance Agency (FHFA) ranging from 1975 to 2016. In Figure A.1 year on year changes of the quarterly house prices index are depicted. The first impression is that there are three cycles in the sample with peaks in 1979, 1986 and 2005. To detect the number and timing of cycles based on a formal test we employ the multiple breakpoint test of Bai and Perron (2003). For this purpose we estimate an equation of the annual changes in house prices using the first and fourth lag as regressors. Afterwards we apply the global test of a certain number of break points versus no break points to the coefficients of this regression. We find a maximum number of five breaks at 1983q3, 1990q1, 1996q3, 2005q4 and 2011q4. The first break date corresponds with a trough, because we lost the first observations due to the testing procedure. To be able to date the first cycle of our sample we refer to Igan and Loungani (2012), who date the peak to 1979q4. Based on this procedure we are able to formally date the three housing cycles. This is in line with the literature, in particular Igan and Loungani (2012) and Sinai (2012).

The description of the nationwide developments of house prices covers the considerable heterogeneity of across states. However, most empirical studies find that some of the greatest divergences occur between coastal states and interior states but the composition of these two groups differs across studies to some extent. For this reason we proceed by looking at the annual changes of the quarterly state level house prices indices from FHFA from 1976 to 2016 (Figure A.2 and Figure A.3). Most interesting for our study are the similarities between the cycles in the aggregate index and in the indices for the states. An important finding is that there are only a few states in which house prices cycles correspond with the nationwide cycle. In particular, we find all three cycles in California, Massachusetts, Nevada, New Hampshire, New Jersey, Oregon, Pennsylvania Rhode Island, Vermont, Virginia and Washington. All of these states can be grouped as coastal states, with the exception of Nevada. At least Nevada has a long boarder to California which makes it likely that a ripple effect from California occurs (Gupta and Miller, 2012). In all other states at least one of the nationwide cycles is not clearly visible in the data. In most cases this is the cyclethat ranges in the aggregate date from 1989 to 1996.

It is also evident that the volatility of house price growth rates varies considerably across states. In Alabama, Georgia, Kansas, Nebraska, North Carolina, and Ohio house price changes ranges from minus ten to plus ten percent over the whole sample. Most of these states are grouped as interior states. Exceptions are Georgia and North Carolina. In states like New York, Washington, Pennsylvania, and Louisiana inflation rates ranges between minus ten and plus twenty percent. In states like New Hampshire, and Alaska house price changes between minus 30 and plus forty percent. Most of these states are coastal states but the distinction is not so evident.

Moreover, there are substantial differences in volatility over time. In North Dakota, South Dakota, Maine, Alaska and West Virginia changes in house prices were much more pronounced until the end of the eighties. Afterwards the volatility is much lower. In contrast, in Arizona, Florida, California and Virginia volatility increased towards the end of the sample.

The overall picture is that there is a group of mainly coastal states that exhibit the same house price cycles as the nationwide index. The other states contribute to some but not all of the nationwide cycles and with regard to changes in volatility to a varying amount. It is therefore interesting to analyze whether there are economic factors that are related to the differences in house price dynamics across states.

To answer this question Reichert (1990) uses a demand and supply framework for a housing market to identify factors that may cause differences in house price dynamics across regions. He argues that differences in demand factors for housing account for the differences in price developments. In particular he finds that the total level of resident population is an important demand factor. In addition, economic factors like employment as well as income are able to explain differences in house price dynamics.

In an analysis of the recent house price cycle Cohen et al. (2012) found that changes in land prices were more important for the house price boom than changes of housing structure. This could indicate that the scarcity of land was important for the magnitude of house price increases. Therefore, states which are better characterized by urban areas should show stronger increases in house prices than states which are dominated by rural areas. In addition, Capozza et al. (2004) find additional evidence that supply factors of housing markets are important for the house price dynamics. They argue that the magnitude of price changes after a shock are smaller if the housing stock can be adjusted quickly and at low costs. In line with this hypothesis these authors find that high construction costs and faster growth in population as well as income are associated with a greater likelihood that house prices overshoot their long-run equilibrium levels.

The interpretation of this finding is, that a higher autocorrelation is associated with a greater likelihood of overshooting the equilibrium price. An important factor for the construction cost is land availability. Again, in urban areas where building land is scarce construction costs are higher. One variable that might indicate the scarcity of land is the population density. In crowded areas there is less space to build new houses. This might be the case in some coastal regions. This is in line with Glaeser et al. (2014) who argue that coastal housing markets have a high inelastic supply while interior markets have very elastic supply of homes.

One of the few studies that try to group similar regional entities by statistical techniques is Hernandez-Murillo et al. (2017). These authors analyze the housing cycles by using building permits as the endogenous variable. In this approach they choose a set of determinants that are related to demand, supply, geographical or financing conditions. In particular they use housing units per square km, population growth, manufacturing employment share, average winter temperature, unemployment rate, an index of undeveloped land, an elasticity of land supply and the growth in subprime mortgages. Their results indicate that population growth is an important determinant for the clusters of states.

3. Econometric framework

We use a Markov switching model of Hamilton and Owyang (2012) to analyze the properties of a national house price cycle based on state level house price data. This approach allows us to model explicitly the evidence that there are considerable differences in the house price dynamics between groups of states by incorporating clusters of region as an additional regional entity. Within this framework a nationwide house price cycle occurs when house prices in all states are in the same cyclical phase. For example in a nationwide house price boom all house prices increase and in a nationwide bust house prices fall in all states. This approach allows that a reduction of house prices occurs only in a cluster of states. Moreover, which states belong to such an idiosyncratic cluster is estimated endogenously by our econometric framework.

To be more precise, let $\boldsymbol{y}_t = (y_{t1}, \ldots, y_{tN})'$ be an $(N \times 1)$ vector, where y_{tn} denotes the house price growth rate for state n observed at date t and N denotes the number of states. It is assumed, as in Früwirth-Schnatter and Kaufmann (2008), that reduction of house prices can be characterized by a small number K of different clusters of regions. An aggregate indicator $z_t \in 1, 2, \ldots, K$, which follows a Markov switching process, determines which cluster is in house price bust at date t. Each cluster k is associated with an $(N \times 1)$ vector $\boldsymbol{h}_k = (h_{1k}, \ldots, h_{Nk})'$ whose nth element is unity when state n is associated with cluster k and zero otherwise. When $z_t = k$, all states associated with cluster k would be in a house price bust. The model of Hamilton and Owyang (2012) can be written as

$$\boldsymbol{y}_t = \boldsymbol{\mu}_0 + \boldsymbol{\mu}_1 \circ \boldsymbol{h}_k + \boldsymbol{\epsilon}_t, \tag{1}$$

where the nth element of the $(N \times 1)$ vector $\boldsymbol{\mu}_0 + \boldsymbol{\mu}_1$ is the average house price growth in state n during a house price bust and the nth element of the $(N \times 1)$ vector $\boldsymbol{\mu}_0$ is the average house price growth in state n during expansion. It is assumed that $\epsilon_{tn} \sim$ i.i.d. $N(0, \sigma_{nt}^2)$, with $\boldsymbol{\epsilon}_t$ independent of $\boldsymbol{z}_\tau$ for all dates and $\boldsymbol{z}_t$ follows a Markov switching process with $K \times K$ transition matrix $\boldsymbol{P}$. The transition matrix $\boldsymbol{P}$ contains the transition probabilities for the regimes, with row i, column j element

$$p_{ji} = p(z_t = j | z_{t-1} = i), \tag{2}$$

where, as in Hamilton (1994) each column of $\boldsymbol{P}$ sums to unity.

Figure (A.1) reveal that the house price series are very volatile. A time-varying variance of the error term in our model may erroneously be characterized by a fast switching between regimes. Therefore, we allow σ_{nt} to vary over time. We extent the model of Hamilton and Owyang (2012) by letting the standard derivations σ_{nt} evolve as geometric random walks

$$\log \boldsymbol{\sigma}_t = \log \boldsymbol{\sigma}_{t-1} + \boldsymbol{\eta_t}, \tag{3}$$

where $\boldsymbol{\eta}_t \sim N(\boldsymbol{0}, \boldsymbol{W})$ with $\boldsymbol{W}$ being a diagonal matrix.

Following Hamilton and Owyang (2012) and (Hernandez-Murillo et al., 2017) we impose two configurations for $\boldsymbol{h}_K$ and $\boldsymbol{h}_{K-1}$ a priori, imposing that $\boldsymbol{h}_K$ is a vector of all zeros (so that every state is in expansion when $\boldsymbol{z}_t = K$) and $\boldsymbol{h}_{K-1}$ is a vector of all ones (every state is in a house price bust regime when $\boldsymbol{z}_t = K-1$). The configurations for the other $K-2$ clusters are estimated from the data. Based on the results of the cross validation test (Table B.3) we will use $K = 3$ in the empirical application. Thus we have an additional idiosyncratic cluster. Finally, it is assumed that a $(d \times 1)$ vector $\boldsymbol{x}_{nk}$ influences whether state n is in a house price bust when $z_t = k$ according to

$$p(h_{nk}) = \begin{cases} \frac{1}{1+\exp(\boldsymbol{x}'_{nk}\boldsymbol{\beta}_k)} & \text{if } h_{nk} = 0 \\ \frac{\exp(\boldsymbol{x}'_{nk}\boldsymbol{\beta}_k)}{1+\exp(\boldsymbol{x}'_{nk}\boldsymbol{\beta}_k)} & \text{if } h_{nk} = 1 \end{cases} \tag{4}$$

for $n = 1, \ldots, N; k = 1, \ldots, K-2$. This allows us to estimate which characteristics states have in common, which share a regional house price cycle.

3.1. Prior specification

We adopt a Bayesian approach and estimate the posterior distributions via the Gibbs sampler as described in Hamilton and Owyang (2012). The only difference is that we do not draw the variance from an Gamma distribution, but instead use the algorithm of Kim et al. (1998)[1] to draw the stochastic volatility. In order to obtain the posterior distributions, we now specify our prior for the model coefficients to combine it with the likelihood function. We use independent normal priors across states for $\boldsymbol{\mu}_n = (\mu_{n0}, \mu_{n1})'$:

$$\boldsymbol{\mu}_n \sim N([1, -2]', 10 \times \boldsymbol{I}_2) \quad n = 1, \ldots, N, \tag{5}$$

and for $\boldsymbol{\beta}_k$:

$$\boldsymbol{\beta}_k \sim N(\mathbf{0}_d, 10 \times \boldsymbol{I}_d) \quad k = 1, \ldots, K-1. \tag{6}$$

The variance for these priors are set to large values, in order to use relative uninformative priors. For the transition matrix P we adopt a Dirichlet prior

$$\boldsymbol{P} \sim D(\boldsymbol{\alpha}), \tag{7}$$

where all elements of $\boldsymbol{\alpha}$ are set to unity. This corresponds then to a uniform prior, also called Laplace prior. We use independent inverse Gamma prior for the state covariance matrix $\boldsymbol{W}$

$$\boldsymbol{W}_{n,n} \sim IG(v, u), \tag{8}$$

for $n = 1, \ldots, N$, where IG denotes the inverse Gamma distribution. We follow Primiceri (2005) among others by setting $v = 3$, so that the inverse Gamma prior has finite mean and variance and $u = 0.0001$ in order to regularize the degree of time-variation in the variance. Finally we set relatively non-informative values on the initial condition for $\log \boldsymbol{\sigma}_t$

$$\log \boldsymbol{\sigma}_0 \sim N(\mathbf{0}_n, 10 \times \boldsymbol{I}_n). \tag{9}$$

3.2. Cross Validation

In order to estimate the model, the number of clusters needs to be specified. We chose the number of clusters by using cross-validation, which computes a quasi-out-of-sample score by estimating the model with a subset of data and validating the omitted data. The full data set $\boldsymbol{Y}_T$ is partition into R blocks,

$$\boldsymbol{Y}_T = [\mathcal{Y}_1 \quad \mathcal{Y}_2 \quad \ldots \quad \mathcal{Y}_R] \tag{10}$$

[1]Note that we take into account the corrigendum of Del Negro and Primiceri (2015) in our code.

for

$$\mathcal{Y}_r = [\boldsymbol{y}_{t_r} \quad \boldsymbol{y}_{t_{r+1}} \quad \dots \quad \boldsymbol{y}_{t_r - 1}], \tag{11}$$

and the full set of observations with block $\mathcal{Y}_r$ deleted is denoted as

$$\mathcal{Y}^{(r)} = [\mathcal{Y}_1 \quad \dots \quad \mathcal{Y}_{r-1} \quad \mathcal{Y}_{r+1} \quad \dots \quad \mathcal{Y}_R]. \tag{12}$$

Define $\mathcal{Z}^{(r)}$ in the same way as a matrix of realization for $\boldsymbol{Z}_T$ with block r deleted:

$$\mathcal{Z}^{(r)} = [\mathcal{Z}_1 \quad \dots \quad \mathcal{Z}_{r-1} \quad \mathcal{Z}_{r+1} \quad \dots \quad \mathcal{Z}_R]. \tag{13}$$

This partition allows us to judge how well a particular model, that was estimated only on data $\mathcal{Y}_r$, predicts the values of $\mathcal{Y}^{(r)}$. We do so by generating as series of M draws from the posterior distribution conditional on only $\mathcal{Y}_r$. Conditional on a particular draw of $\{\mathcal{Z}^{[r,m]}, \boldsymbol{P}^{[r,m]}\}$, where $m = 1, \dots, M$, we generate a draw from the distribution of $\{\mathcal{Z}_r\}$, for details see Hamilton and Owyang (2012). A draw of $\{\mathcal{Z}_r\}$ for observation t lets us calculate a forecast $\boldsymbol{m}_{z_t^{[r,m]}}$ for observation $\boldsymbol{y}_t$. We then select the model, which delivers the smallest sum squared error (SSE) calculated as

$$SSE = \frac{1}{M} \sum_{m=1}^{M} \sum_{r=1}^{R} \sum_{t=t_r}^{t_{r+1}-1} (\boldsymbol{y}_t - \boldsymbol{m}_{z_t^{[r,m]}})'(\boldsymbol{y}_t - \boldsymbol{m}_{z_t^{[r,m]}}). \tag{14}$$

4. Empirical Results

For our analysis of regional house price cycles we use seasonally adjusted quarter-to-quarter growth rates of house prices for the states in the US. Our source is the Federal Housing Finance Agency for 49 states. The sample ranges from 1975:Q2 to 2017:Q4. It is obvious from Figure A.5 that in most states the volatility is high at the beginning of the sample and recedes towards the financial crisis. This is clear evidence that the volatility varies considerably over time, a property that we capture by the empirical model.

4.1. Housing cycles

To describe house price cycles within our empirical framework, it is crucial to choose the number of clusters. Table B.1 reports the cross-validation results using $R = 10$ sub-samples. The model with one idiosyncratic cluster delivers the best out-of-sample forecast performance, revealing that the house price cycle is homogenous up to one cluster.

Based on this model we identify three different regimes in the growth rates of house prices (Figure A.6). We call the first regime the nationwide boom because in this phase house prices in all states are rising. This regime is prevalent most of the time in our sample. Apart from this, we find two regimes where house prices are falling. The first of them we call spatially limited bust regime. There, house prices fall in California and the east coast states e.g. New York. The third regime, the national bust, is characterized by dropping house prices all in all states. This regime occurs for the first time at the second quarter 2008 and therefore one quarter before the beginning of the Great Recession.

The differences in the transition between the cycles are also visible in the transition probabilities between the regimes (Table B.2). This highlights the uniqueness of the recent house price bust. The first two housing cycles show that house prices usually increase over long periods. The probability to stay in the boom regime from one period to the next is 0.9. If the boom regime ends, the probability for the spatially limited bust regime is 0.08 and therefore higher than the probability to switch from a national boom to a national bust, that has a probability of 0.01.

Figure A.4 shows that most of the coastal states are included in this idiosyncratic cluster.[2] Eight of these twelve states show all three cycles that are found in the aggregatehouse price index. Furthermore, Table B.3 shows the posterior medians and means for the model parameters, μ_0 and μ_1. The differences between the means of the two regimes are substantially larger than for most of the states that are not included in this cluster. This indicates that states of this idiosyncratic cluster show pronounced cycles in house prices.

4.2. What establishs the idiosyncratic cluster?

Within the two house price cycles prior to the great recession house prices only drop in a small group of states. Nevertheless, these downturns are visible in the nationwide house price cycle. To understand nationwide house price dynamics, it is important to get a wider picture of the common characteristics of the states that belongs to this cluster and the difference to all other states.

[2]In particular, California and the north east coastal states like Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont and Virginia belong to this cluster.

We identify these common features within the idiosyncratic cluster estimating a logit model. To analyse the factors that increase the likelihood of a state belonging to this cluster we select variables from different areas like population, economics, housing and banking. Whenever possible, we use sample averages of time periods that are comparable to our house price time series. However, in many cases sample sizes are much smaller than the time period use in the Markov-Switching model. Nevertheless, in this cases we decided to include the variables to cover a wide area of explanatory variables.

The population situation within the states is characterized by population growth and population density. We calculate the population growth rate from 1970 to 2010. As a measure of population density we use averages of the years 1970 to 2010 that are taken from Census Bureau. Reichert (1990) point out that an increasing population is accompanied to a high demand for housing. However, our preferred variable is population density because this variable additionally includes aspects of housing supply: For instance, it is likely that in states with a high population density it is more costly and time consuming to increase the housing stock after a positive demand shock. The additional variables income and the unemployment rate are related to housing demand because favorable economic conditions like high personal income and a high level of job security promote a higher demand for housing.

The economic conditions in the states are described by the personal income from the Census Bureau for as averages of the years 2000, 2010 and 2015. The state level unemployment rate is from BLS. We take the average from 1976 to 2019.To get an idea whether differences between house price development can be explained by differences in the business cycle, we calculate the correlation between the growth rate of house prices and the growth rate of state level GDP (GDP correlation). State level GDP data is available at the BEA from 2005 to 2019.

The housing conditions at the state level are depicted by the housing density on average of the years 1970 to 2010 from the Census Bureau. Another indicator of housing supply is the Saiz (2010) housing supply elasticity. This author finds that land constraint metropolitan areas show an inelastic housing supply after a demand shock. Saiz estimated this elasticity for metropolitan areas only. We obtained state level data by averaging the metropolitan areas of a state.

It is also possible that the availabiliy of loans differ across states. Therefore, we include the loan concentration for residential real estate (median percent of qualifying total capital) from FDIC. This is a measure of banks exposure in this credit class. An additional indicator of banks ability to lend is the net loans to assets ratio also taken from the FDIC. For both indicators we use the average value of the years 2017 and 2018. The same holds for our figure of commercial real estate loans.

The results of the logistic regression are presented in Table B.4. The main feature is that states within the idiosyncratic cluster switch to a regime with declining house prices after a regime of a national boom. Moreover, it is shown that it is statistically credible that a higher population density increases the likelihood that a state belongs to the idiosyncratic cluster . In this regard population density seems to be a scarcity indicator. The unemployment rate is an indicator of economic powers of a state. A lower unemployment rate is accompanied with higher housing demand. The interpretation of housing density is less obvious. One interpretaton is that housing density is a measure of scarcity. In this case we should expect the same sign in our regression as population density. Another interpretaton is that housing density is a quality measure of housing, as consumers often prefer low density neighbourhoods in suburban areas and are willing to pay a premium (Song and Knaap, 2004). The last significant variable is Saiz' elasticity. A higher elasticity reduces the likelihood of belonging to the idiosyncratic cluster. Saiz finds that supply elasticities are functions of physical and regulatory constraints, hence stronger constraints lead to a more inelastic housing supply.

The overall result of this analysis is that pronounced boom-bust cycles in house prices predominately takes place in states that are economically attractive, with a relatively high population density, a relatively low housing density and some constraints in the supply of housing.

4.3. House price bubbles during the cycles

The finding that the states of the idiosyncratic cluster experienced strong demand and a restricted supply of housing is one explanation of strong increases of house prices. In contrast, they cannot explain the drop in house prices that is the main characteristic of this cluster. However, there is some evidence in the literature that the recent house price bust was generated by a house price bubble in the US housing market (Negro and

Otrok, 2007). However, it is also argued that not one bubble occurred but several. Strong increases are one prerequisite for the occurence of a houce price bubble. If house price increases lead to exaggeration this could be the reason for the recurrent cycles in the idiosyncratic cluster.

In this section we test for bubbles in the state level house price series using the generalized supremum ADF (GSADF) test (Phillips et al. (2015)).[3] The GSADF is based on a recursive testing procedure that calculates a test statistic and the corresponding critical value for each observation of the time series. However, some observations are needed to initialize the procedure. In this test the null hypothsesis of a unit root is tested against the alternative of a mildly explosive autoregressive process. The results of this testing procedure for the state house price indices are presented in Figure A.7. Test statistics above the critical values indicate a rejection of the null hypothesis. This is evidence of a bubble period in this time series.

Due to the recursive procedure for the bubble test it is not enough data available to get clear evidence of state level house price bubbles during the first house price cycle. During the second house price cycle (from 1984 to 1997) we find that most of the states included in the idiosyncratic cluster show a significant sign of a bubble based on our test statistic. In contrast, most states not included in this cluster do not show signs of a bubble in the late eighties. Exceptions are Louisiana, Oklahoma, Texas and Washington. Again, the correspondence of the house price cycle in the cluster states as well as in the national index is important for the house price developmet in the whole country.

During the house price cycle that led to the financial crisis, the empirical results are different. The bubble tests reveal significant indication of a bubble around the years 2005 and 2006 for most of the states. As in the previous cycle, all states except California exhibit signs of a bubble during this period. In additon, the tests for Alaska, New Mexico, Wyoming and Florida indicate clearly a bubble in house prices. The only exceptions are Colorado, Iowa and Nebraska. Moreover, the tests indicate a lot of other bubble periods in one state or a small group of states. However, these episodes are not visible at the national level and therefore best described as idiosyncratic events.

The occurrence of bubbles help to explain the differences between the two cycles. During the cycle of the eighties and nineties the cycle was driven by a bubble in the coastal

[3] This test is available by the RTADF EViews Add-in Caspi (2017).

states of the idiosyncratic cluster. Therefore, the national boom was followed by a bust in the states of the idiosyncratic cluster. The housing cycle that lead to the financial crisis took place in almost all states indicated by the switch from the national boom to the national bust regime. This, in addition to the magnitude of the drop in house prices accounts for the strong real effects compared to former house price busts.

5. Conclusion

In this paper we contribute to the discussion about the importance of national and idiosyncratic factors to house price cycles in the US. Our approach allows for a common cycle in all US states and for cycles in certain clusters of states. Moreover, we allow for time-varying volatility in the house prices. An assumption that is clearly supported by the data. We use population density, income and unemployment rate to identify house price clusters at the state level.

We find that in particular house price increases take place in all states. In contrast, busts typically occur in some states only. In particular, coastal states like California and New York, Rhode Island etc. show the same cycle as the nationwide index but normally more pronounced than the nationwide index. This cluster of states is characterized by a higher population density, lower unemployment rate, lower housing density and smaller land supply elasticity. This constellation of variables indicates a strained housing market and explains the high price volatility.

Busts in the coastal states are sufficient to end house price cycles at the national level. To detect nationwide house price cycles it is therefore sufficient to observe price developments in the coastal states. The advantage is that house price cycles are more pronounced in these states than at the national level. This may increase the possibility to detect turning points that are relevant for the national cycle. However, this question is left for future research.

For a better understanding of the house price dynamics we performed recursive bubble tests. The results show that the uniqueness of the recent house price bust that led to the financial crisis coincide with the burst of house price bubbles in most of the states. This was the only period in the sample were a national bust regime occurred in the US. During the preceding house price cycle bubbles occurred only in the states of the idiosyncratic cluster. This result supports to the findings of Negro and Otrok (2007). These authors estimate a common factor of state level house price data. They find that previous to the financial crisis house price movements are mainly driven by local phenomenon. In contrast, during the recent financial crisis the increase on house prices is a national phenomenon.

Two conclusions can be drawn from this result. The first is that the occurrence of a nationwide bust regime is a very unlikely event. However, the second conclusion is that if the housing sector turns into the national bust regime this is a clear indication for a severe crisis in the housing market. The distinction between the two bust regimes show the uniqueness of the recent housing market crisis. Earlier cycles in housing prices are mainly located in some states at the east and the west coast of the US. Housing markets are not affected by these cycles. This reduced the countrywide real economic effects of the housing cycles.

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Appendix A. Figures

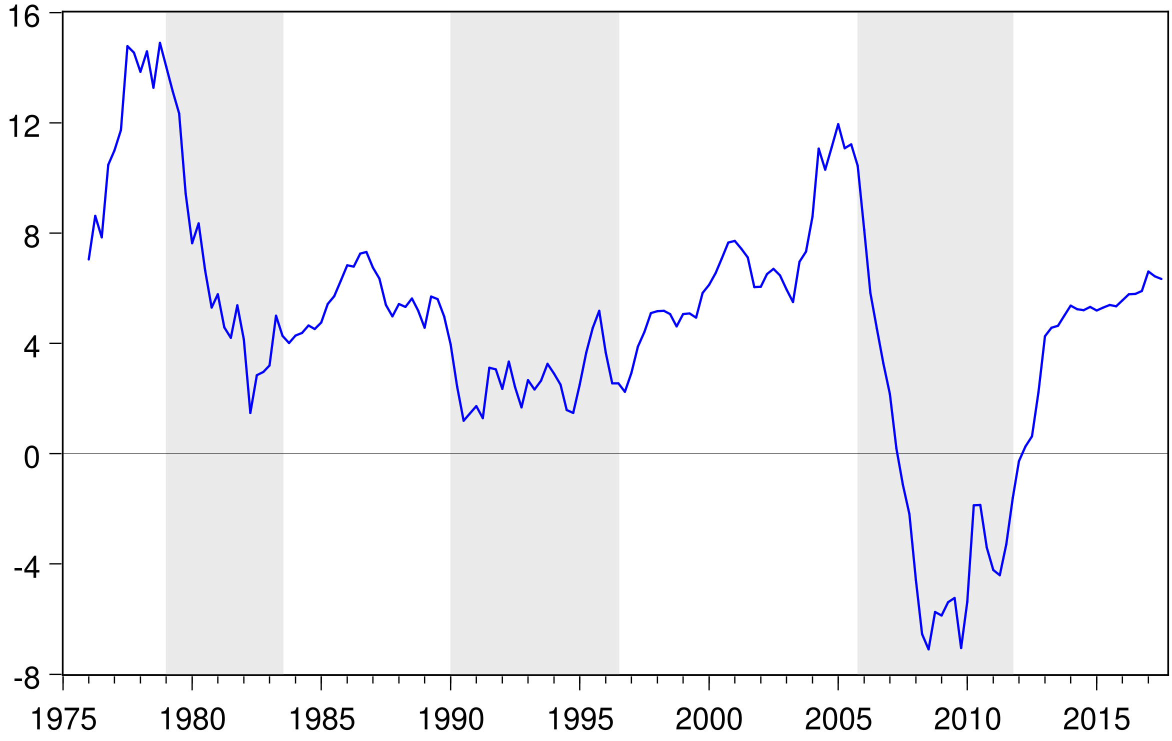

Figure A.1: Cycles in US house prices

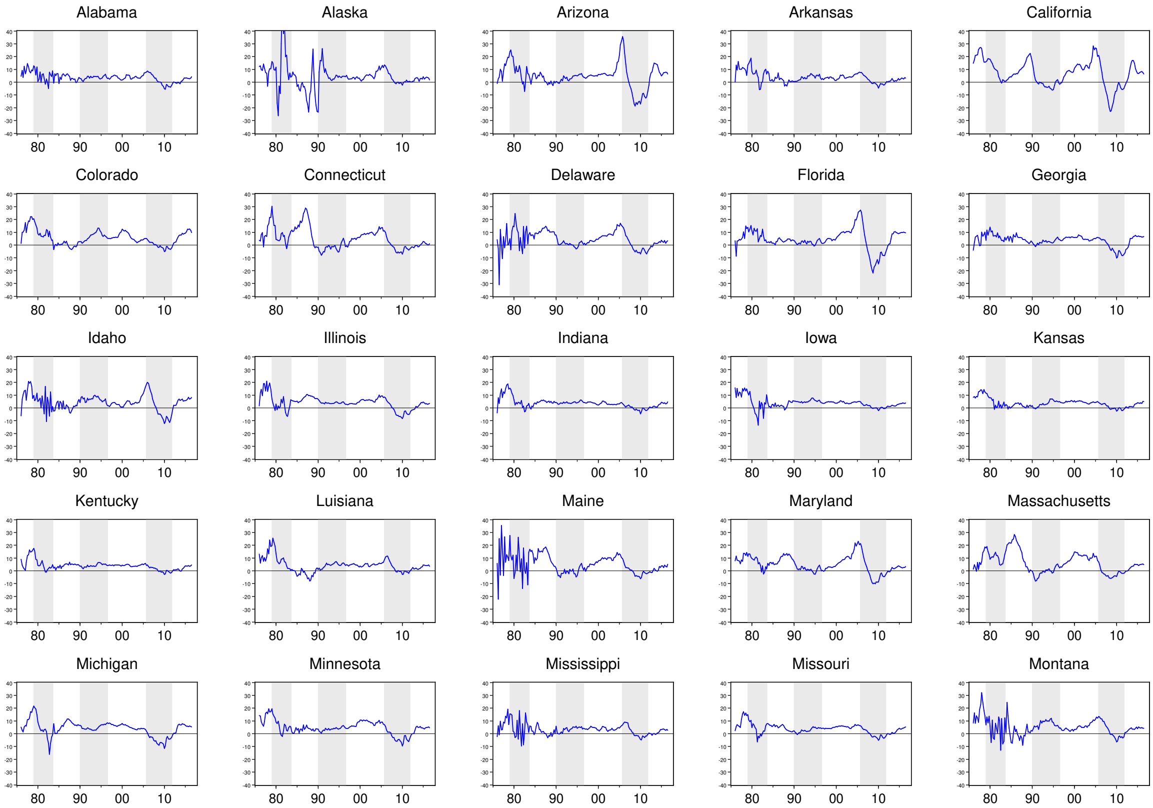

Figure A.2: State level house prices 1

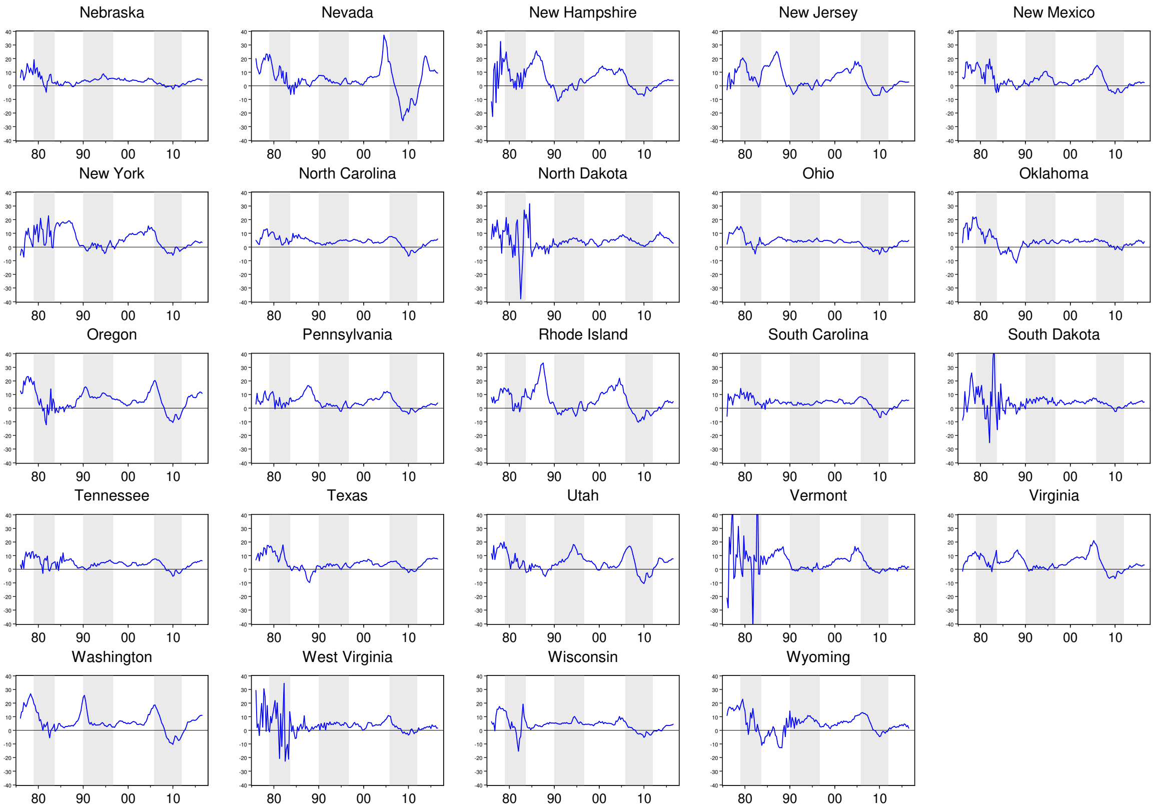

Figure A.3: State level house prices 2

Figure A.4: States belonging to the diosyncratic cluster

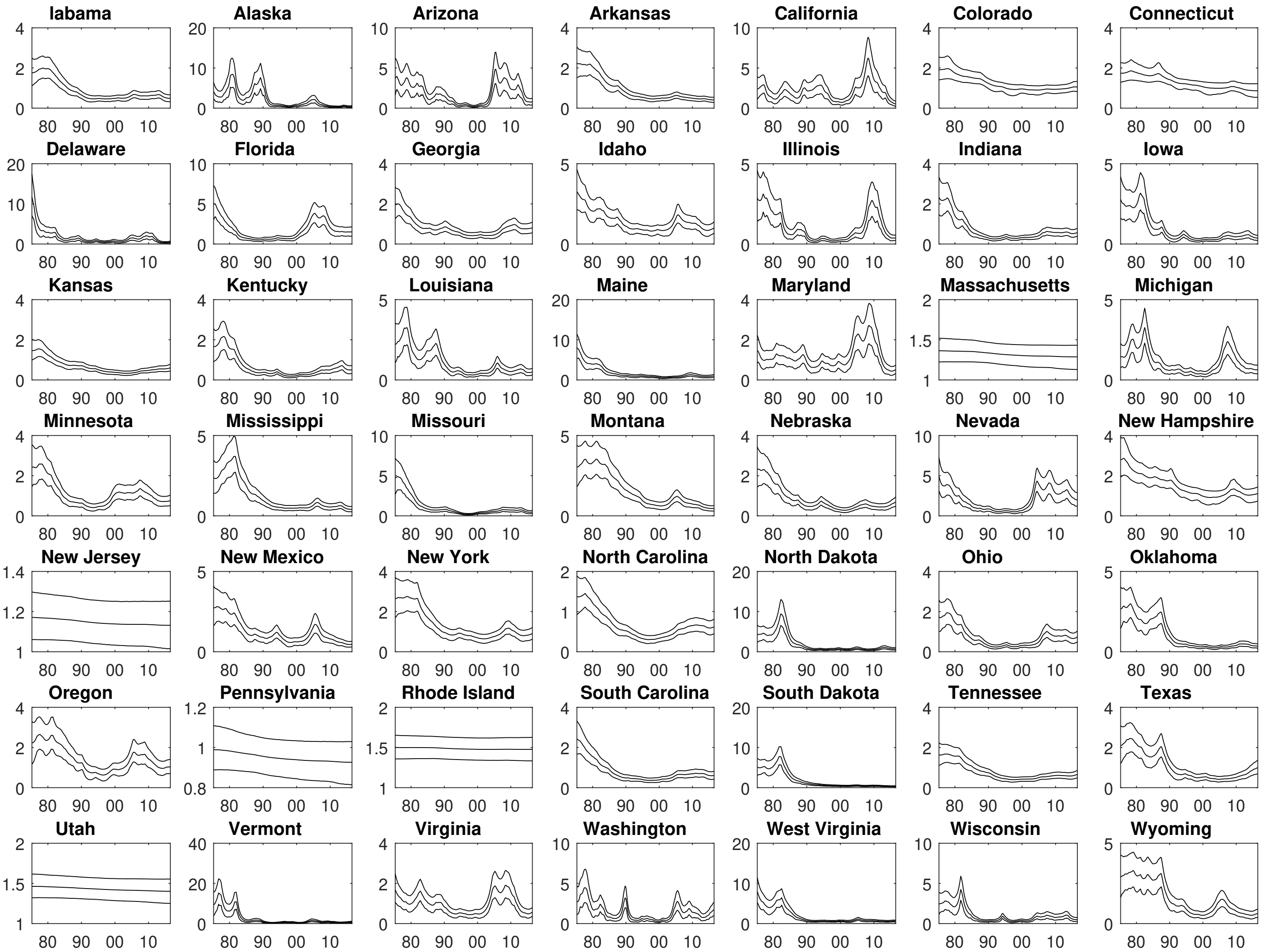

Figure A.5: Volatilities for the states, with 90% error bands.

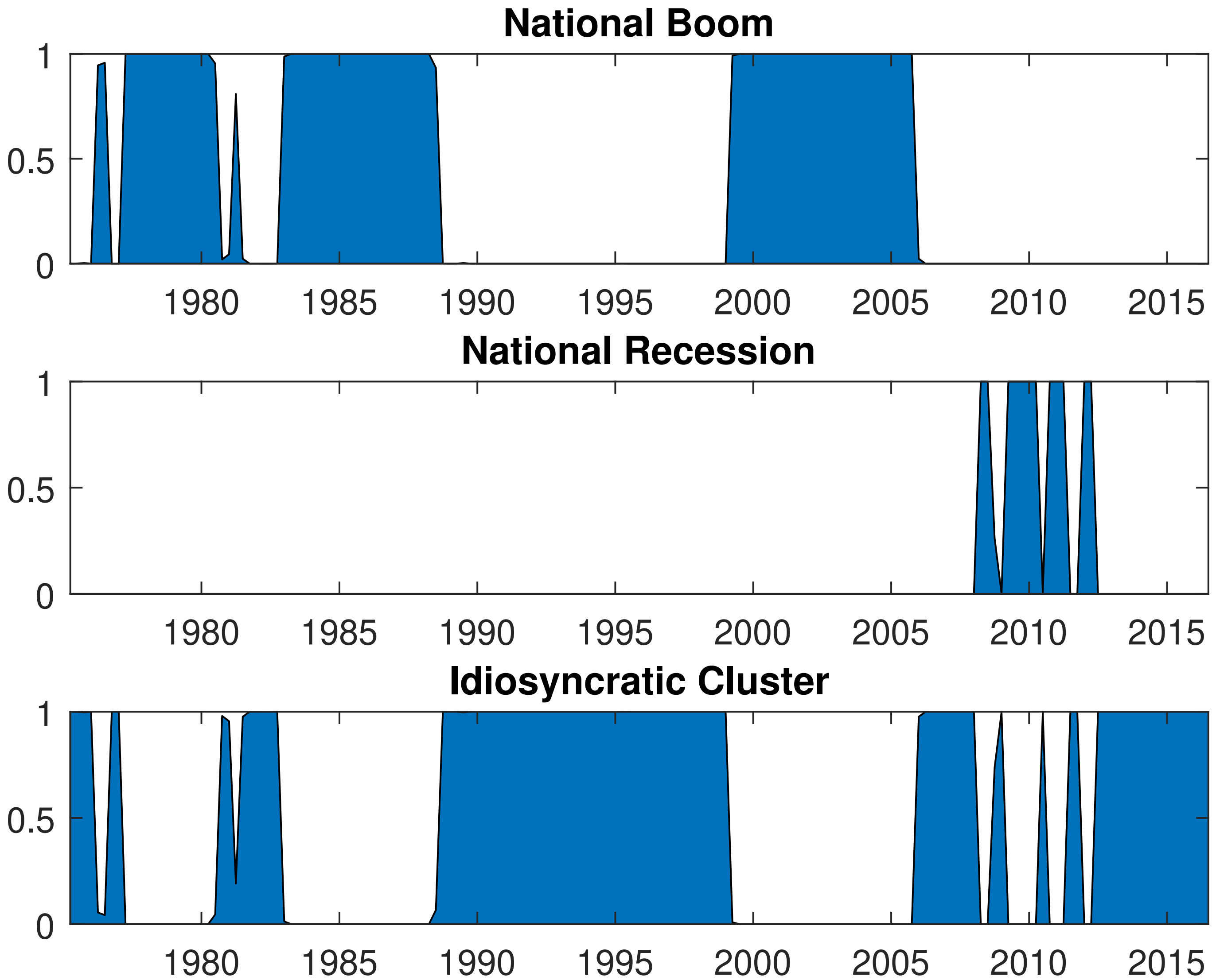

Figure A.6: Cycles in US house prices

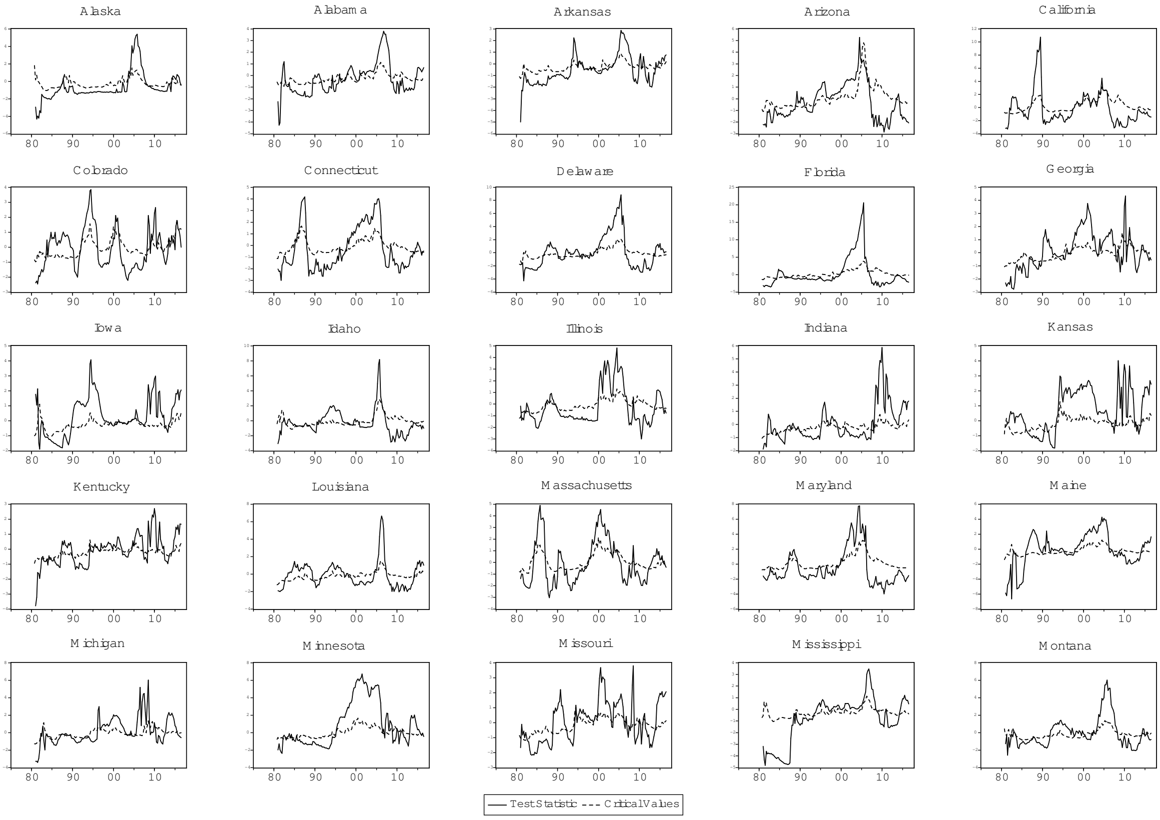

Figure A.7: House price bubble tests 1

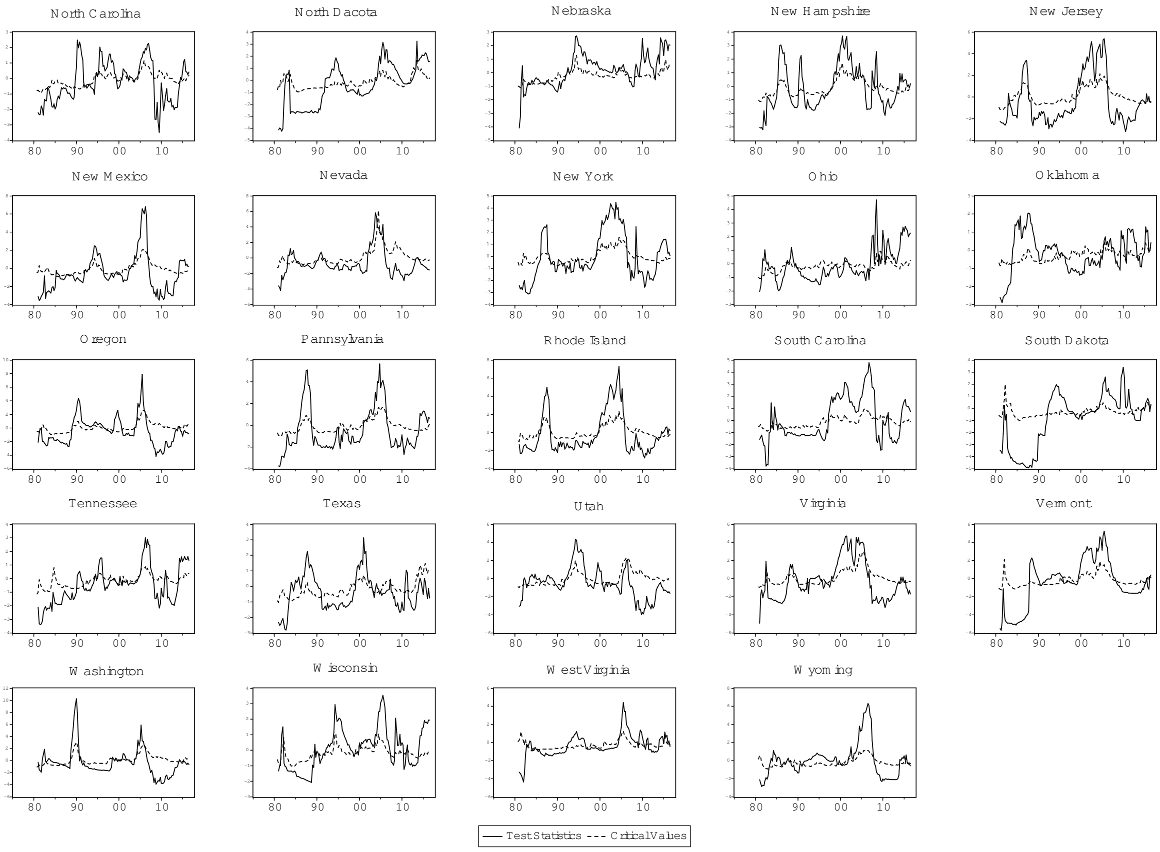

Figure A.8: House price bubble tests 2

Appendix B. Tables

Table B.1: Cross Validation Results

	Number of Idiosyncratic Cluster				
	1	2	3	4	5
SSE	34364	36146	36982	36355	36517

The SSE is calculated as defined in (14).

Table B.2: Mean Regime Transition Probabilites

	From Boom	From Bust	From Cluster 1
To Boom	0.9028	0.0658	0.0164
To Bust	0.0144	0.7074	0.0532
To Cluster 1	0.0828	0.3267	0.8854

This table shows the estimated transition probabilities as defined in (2).

Table B.3: The individual states

		Mean		5% Quantile		95% Quantile	
States	h_1	μ_0	μ_1	μ_0	μ_1	μ_0	μ_1
Alabama	0	0.90	-1.86	0.81	-2.18	0.99	-1.55
Alaska	0	0.77	-0.95	0.68	-1.15	0.86	-0.76
Arizona	0	1.28	-4.60	1.20	-5.80	1.37	-3.30
Arkansas	0	0.83	-1.52	0.75	-1.78	0.93	-1.52
California	1	1.90	-3.24	1.72	-4.25	2.08	-2.27
Colorado	0	1.45	-2.35	1.27	-2.82	1.62	1.88
Connecticut	1	2.75	-2.86	2.39	-3.32	3.13	-2.40
Delaware	1	2.06	-1.61	1.79	-1.95	2.37	-1.31
Florida	0	0.91	-3.58	0.76	-4.57	1.06	-2.62
Georgia	0	1.17	-3.29	1.06	-3.75	1.27	-2.85
Idaho	0	1.24	-3.56	1.05	-4.20	1.42	-2.91
Illinois	1	1.51	-0.66	1.41	-0.78	1.63	-0.54

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Table B.3 – continued from previous page

States	h_1	Mean μ_0	Mean μ_1	5% Quantile μ_0	5% Quantile μ_1	95% Quantile μ_0	95% Quantile μ_1
Indiana	0	0.93	-1.69	0.87	-1.98	0.99	-1.42
Iowa	0	1.03	-1.32	0.95	-1.54	1.09	-1.09
Kansas	0	0.94	-1.48	0.85	-1.73	1.03	-1.24
Kentucky	0	1.02	-1.53	0.97	-1.78	1.08	1.28
Louisiana	0	1.06	-1.52	0.97	-1.80	1.14	-1.24
Maine	1	2.46	-2.15	2.26	-2.47	2.67	-1.84
Maryland	1	2.21	-1.62	1.92	-1.94	2.50	-1.31
Massachusetts	1	3.10	-2.75	2.82	-3.11	3.38	-2.37
Michigan	0	1.43	-3.13	1.30	-3.75	1.55	-2.54
Minnesota	0	1.11	-2.86	0.99	-3.38	1.24	-2.35
Mississippi	0	0.84	-1.72	0.73	-2.02	0.94	-1.43
Missouri	0	1.06	-2.10	0.99	-2.45	1.13	-1.76
Montana	0	1.21	-2.09	1.08	-2.48	1.34	-1.70
Nebraska	0	0.91	-1.21	0.84	-1.45	0.99	-0.97
Nevada	0	0.87	-4.93	0.71	-6.30	1.04	-3.52
New Hampshire	1	2.76	-2.59	2.50	-3.02	3.04	-2.15
New Jersey	1	3.11	-3.07	2.87	-3.36	3.35	-2.77
New Mexico	0	0.74	-2.04	0.60	-2.44	0.89	-1.66
New York	1	2.62	-2.33	2.41	-2.64	2.85	-2.03
North Carolina	0	1.05	-2.19	0.97	-2.51	1.12	-1.87
North Dakota	0	1.05	-0.54	0.92	-0.84	1.21	-0.18
Ohio	0	1.02	-2.14	0.96	-2.52	1.08	-1.77
Oklahoma	0	0.97	-1.23	0.90	-1.44	1.03	-1.03
Oregon	0	1.70	-3.72	1.51	-4.37	1.89	-3.05
Pennsylvania	1	2.04	-1.63	1.84	-1.88	2.04	-1.63
Rhode Island	1	3.25	-3.24	2.94	-3.61	3.55	-2.85
South Carolina	0	1.05	-2.31	0.96	-2.65	1.13	-2.31
South Dakota	0	1.09	-1.22	1.01	-1.46	1.18	-0.99
Tennessee	0	1.05	-1.94	0.97	-2.24	1.14	-1.65
Texas	0	1.00	-1.28	0.89	-1.55	1.12	-1.01
Utah	0	1.46	-3.30	1.27	-3.98	1.64	-2.62

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Table B.3 – continued from previous page

States	h_1	Mean		5% Quantile		95% Quantile	
		μ_0	μ_1	μ_0	μ_1	μ_0	μ_1
Vermont	1	1.93	-1.73	1.78	-1.97	2.15	-1.53
Virginia	1	2.01	-1.49	1.82	-1.74	2.21	-1.26
Washington	0	1.20	-3.00	1.09	-3.63	1.31	-2.35
West Virginia	0	0.83	-1.44	0.72	-1.77	0.94	-1.12
Wisconsin	0	1.15	-2.21	1.08	-2.59	1.23	-1.83
Wyoming	0	1.05	-1.53	0.88	-1.94	1.05	-1.53

This tables shows which state belong to the idiosyncratic cluster and the estimated average house price growth during a boom and recession for each state.

Table B.4: Estimated Logistic Coefficients

$\boldsymbol{\beta}$	**Mean**	**5% Quantile**	**95% Quantile**
Constant	-0.65	-6.2666	4.9387
Population growth	-0.0485	-0.1466	0.0286
Population density	0.5133**	0.2401	0.8156
Income	-0.0002	-0.001	0.0005
Unemployment rate	-4.5162**	-7.5192	-1.9773
Correlation with GDP	2.3983	-2.9806	8.4034
Housing density	-0.9922**	-1.6463	-0.432
Saiz elasticity	-7.2498**	-10.7735	-3.7021
Residential real estate	0.0283	-0.0024	0.0678
Net loans to assets	0.7023**	0.2009	1.2478

This table shows the estimate coefficients of the logistic regression in equation (4).