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Clustered Housing Cycles

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Using a panel of U.S. city-level building permits data, we estimate a Markov-switching model of housing cycles that allows for idiosyncratic departures from a national housing cycle. These departures occur for clusters of cities that experience simultaneous housing contractions. We find that cities do not form housing regions in the traditional geographic sense. Instead, similarities in factors affecting the demand for housing (such as average winter temperature and the unemployment rate) appear to be more important determinants of cyclical comovements than similarities in factors affecting the supply for housing (such as housing density and the availability of developable land).

Keywords: clustered Markov switching, business cycles, building permits, comovements.

JEL codes: E32; R31; C11; C32.

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1 Introduction

Recent macroeconomic research has argued that housing market movements are the source of—rather than the consequence of—business cycle fluctuations.[1] For example, housing was the key instigating component of the recent financial crisis (see Bernanke, 2008) and Leamer (2007) argues that, at a national level, housing *is* the business cycle.[2] While business cycles are typically measured at a national level, housing markets are generally believed to be highly localized.[3] At the subnational level, the relationship between housing and the business cycle is less clear. Indeed, Ghent and Owyang (2010) find that, while housing cycles exist at disaggregate levels, the relationship between business cycles and housing appears to break down at subnational levels.[4] The disconnect generated between the two levels of granularity can present problems for macroeconomic analysis and policy making.[5]

What produces the disconnect between housing and business cycles at different levels of disaggregation? One hypothesis is that a national cycle exists across all housing markets, but this more pervasive cycle is lost in the heterogeneity once the data is disaggregated. In other words, housing cycles may have both a national and regional element (Del Negro and Otrok, 2007). Local deviations from the national cycle can be small timing differentials (i.e., cities are just out-of-sync enough that the average cycle does not match the national cycle) or major departures. In the former case, a pervasive national cycle could be detected once we account for the deviations. If the latter case, city-level cycles could be viewed as idiosyncratic—completely independent of the national cycle.

[1]Housing wealth effects lead to a correlation between housing and consumption expenditures and are typically accompanied by changes in housing investment in the same direction. For example, Davis and Heathcote (see 2005) find that residential fixed investment leads non-housing investment and is more than twice as volatile see .

[2]These empirical regularities have prompted macroeconomic researchers to consider the theoretical underpinnings of housing and the business cycle in general equilibrium models (see Iacoviello, 2005; Iacoviello and Neri, 2010).

[3]A few papers have modeled subnational business cycles (e.g., Carlino and Sill (2001) for regions, Owyang et al. (2005) for states, and Owyang et al. (2008) for cities).

[4]Several papers study housing at the subnational level with mixed results. Glaeser et al. (2011); Del Negro and Otrok (2007) show that the variation in house prices is primarily driven subnational factors rather than national factors, while Moench and Ng (2011) find that national shocks have larger effects on the housing cycle than regional shocks. Stock and Watson (2010) show that although building permits co-move across states, housing market can be uncorrelated across regions. Other studies find that housing markets have become more integrated in the last decade (see Cotter et al., 2012; Kallberg et al., 2014; Landier et al., 2013).

[5]Ghent and Owyang (2010) implies that models need to account for regional differences in U.S. housing cycles, as regional differences may influence optimal policy conduct. Identifying regions with similar housing characteristics would help policymakers more accurately predict cross-regional effects, and identify regions to target with particular policies.

In this paper, we consider city-level construction permits to analyze housing cycles at the regional level. We adapt the model from HO, who identify national and regional business cycle phases. The approach in HO is to allow the data to group states into regions that have the same business cycles. In our model, during the *national* phases, all of the cities will be in expansion or contraction, respectively. Furthermore, cities in the same region (or *cluster*) experience simultaneous idiosyncratic contractions, which could lead, lag, or occur separately from national contractions.

An advantage of the HO model is that it determines the key factors in the grouping of cities—i.e., it generates endogenous (possibly overlapping) clusters or regions. Cities may cluster for economic (e.g., similar industrial composition), geographic (e.g., inability to increase the housing stock due to geographic constraints), or other inherent reasons (e.g., weather). We consider nine covariates in determining our clusters: housing density, population growth, the share of manufacturing employment, average winter temperature, the average unemployment rate, Saiz's (2010) index of undevelopable land and elasticty of land supply, as well as two financial variables reflecting the incidence of subprime mortgages across cities.

We find evidence of a national housing cycle that appears to be linked to the national business cycle. We also find 4 clusters of cities that experience their own idiosyncratic contractions. These contractions can occur before and lead into a national downturn, occur after and prolong a national downturn, or occur completely independently of a national downturn. In addition, our method allows us to determine some of the factors that affect cluster composition. These factors appear to be proxies of city-level housing demand characteristics rather than housing supply characteristics, factors that influence business cycle, or factors related to the similarity of financial conditions.[6]

Our finding that housing cycles may depend on local factors in addition to national factors has implications for policy implementation, as monetary policy may be transmitted in different ways throughout the set of clusters. In fact, Füss et al. (2012) find that MSA-specific demand and supply characteristics, such as population growth and the elasticity of housing supply, are crucial links that transmit national monetary policy and sentiment into housing price inflation at the local

[6]Traditionally, the main driver of house price co-movement is geography. Pollakowski and Ray (1997); Can (1990); Ioannides and Zabel (2003) find positive feedback effects on house prices between contiguous regions and within neighborhoods. Stevenson (2004); Oikarinen (2006) show that co-movements or regional housing markets are driven by substitution effects, where changes in one region's prices generate a time-lag movement in another region's prices. Brady (2011); Holly et al. (2011) also explore the spatial and temporal diffusion of house price shocks in a dynamic system.

level. Therefore, identifying regional clusters of housing cycles represents relevant information for the optimal conduct of monetary policy. We also find a cluster in which financial variables are more important, which suggests that regional differences may influence the conduct of macroprudential policies as well. Our results open up a new line of research to explore whether fiscal policy or macroprudential policies should consider regional differences in attempting to balance out housing cycles across regions and evaluating the heterogeneity in the monetary transmission mechanism.

The rest of the paper is outlined as follows: Section 2 describes the data construction. Section 3 describes the model. Section 4 provides a brief overview of the estimation of the model. Section 5 presents the results and discusses the implications for the determination of the national cycle. Section 6 offers some conclusions.

2 The Data

While much of the recent work has focused on house price dynamics, we are interested in housing as it relates to the business cycle rather than house price dynamics alone. Saiz (2010) argues that housing volumes may be a better indicator of business cycle dynamics than house prices. Indeed, comparing the data on permits and prices reveals important differences in how the two series are connected to the business cycle. Price growth slows during many of the previous downturns but only becomes negative during the 2007-2009 recession. Permits, on the other hand, exhibit clear negative growth rates in all NBER recessions, and therefore represent a more reliable indicator of business cycles. Thus, we show results using city-level permits as our housing indicators; results using prices are available upon request.

In the next subsections, we describe the collection and transformation of the permit data used to construct the cycles and city-level covariates used to form the clusters.

2.1 City-level Building Permits

While city-level building permit data are available for various time periods for the majority of cities, MSA definitions have changed a number of times over the years. These definitional changes can present a problem for business cycle analysis, which requires longer time series to detect switching between phases. Using current MSA-level data for our analysis would limit the number of cities with available data and the length of the time series which only go back to the mid-1990s. Therefore, we construct MSA-level permits by aggregating county-level permits data using the counties included in the December 2009 MSA definitions.[7]

County-level building permits are released monthly as year-to-date levels that accumulate the monthly changes. Although differencing would yield a monthly flow of permits, the year-to-date data are constantly revised, confounding identification of an actual change versus a revision. In addition, the noise in the monthly data affects our filter's ability to detect switches in cycle phase. To mitigate these two problems, we use the band-pass filtered, year-over-year growth rate of the monthly building permits series. This transformation also has the benefit of smoothing outliers that would not be considered business cycle phase changes but could be misidentified by our estimation algorithm.

Our sample consists of data from 1989:01 to 2012:11. We select 135 cities with population greater than 250,000 residents (based on 1990 populations computed with the 2009 MSA definition) for which all covariates and permits data are available. We limit our sample size to large cities because the data for the small cities are inherently noisier, and clustering in larger panels is more computationally-intensive and more likely to be imprecisely estimated.

Figure 1 depicts the building permits growth series for a few of the cities in our sample. The national data are included for comparison; shaded areas represent NBER recession dates. The national data have a clear cyclical pattern that is roughly coincident with the timing of the NBER contractions. The U.S. permits data experience some fluctuations apart from the business cycle dates but the largest downturns begin just before an NBER-defined peak.[8] City-level experiences vary widely: Chicago, for example, behaves very similarly to the nation, while Los Angeles has the same broad features as the nation but has more small, non-national housing contractions. Reno-Sparks NV experiences even more small, non-national housing contractions than LA, such that the series almost appears to exhibit seasonality. Table 8 contains the full list of cities in our sample and summary statistics of the permits growth series.

[7] December 2009 MSA definitions are available from the Census Bureau website `http://www.census.gov/population/metro/files/lists/2009/List4.txt`.

[8] As evidenced by the 2001 recession, permit growth does not always fall with the business cycle. Of course, we have only three national recession experiences in our sample so the results should be extrapolated with caution.

2.2 Covariate Data

In addition to the panel of permits data, we require a set of time-invariant covariates to parameterize the prior that defines the clusters. Our choice of covariates is meant to represent factors that affect housing cycles: demand, supply, geography, economic, and financing conditions. Meen (1999) suggest that co-movements may be caused by factors that affect the demand or the supply of housing. In particular, Meen (1999) finds that co-movements are mainly caused by migration, equity transfers, spatial arbitrage, and local economic development.

Average population growth over the period 1970 to 1990 proxies the average change in housing demand, as higher average population growth suggests a higher average demand for new housing. In addition, the city-level average unemployment rate represents long-run differences in local economic conditions that may also affect the demand for housing.[9] Average winter temperature may be another proxy for housing demand, especially for a higher income demographic.

Housing density is a proxy for the supply of housing, and Saiz's (2010) indexes of undevelopable land reflects geographic constraints on the elasticity in the supply of housing.[10] We also include the share of manufacturing employment because prior studies have shown that it is a determinant of business cycle similarity and may also influence housing cycle similarity.

Finally, we include two measures of credit availability: the change in the proportion of subprime mortgage loans relative to total mortgage loan volume and the growth in the loan volume of subprime mortgages over the period 2002 to 2005.

One limitation of the algorithm described below is that the covariate data used to populate the prior must be time invariant as the model assumes time-invariant clusters. Thus, the cross-sectional covariates are all computed either as long-run averages or by taking a snapshot at some point in the sample. For example, to represent the industrial composition of cities we use the share of manufacturing employment in 1990. Table 1 presents summary statistics of the cross-section of covariates.[11]

[9]Clayton et al. (2010) find evidence that housing demand, in particular, is the main determinant of housing cycles. They find that both house prices and trading volumes are significantly affected by changes in the labor market, which include changes in total non-agricultural employment, average household income, and the unemployment rate.

[10]Expansion of the population away from central urban areas into rural and remote areas (i.e., urban sprawl) is another factor identified in the literature as affecting house price comovement. Rising incomes, growing population, and low commuting costs boost demand for space in distant locations where land is relatively cheap, causing urban expansion. See, for instance Brueckner (2000), Couch and Karecha (2006), and O'Sullivan (2009).

[11]The average population growth is taken from the Census and represents the percent increase in the population

3 The Empirical Model

The model is a first-order Markov-switching model in the mean growth rate of each city's building permits series. We allow for two regimes at the city level: an expansion regime with higher average growth rate and a contraction regime with lower average growth rate. In the most general framework, each city building permit series could have an independent, unobserved 2-state Markov-switching process. In the most degenerate case, each city would have the same business cycle, a national cycle. Each of these models yields a regime process that can be summarized in a single national Markov state variable. In the former case, the Markov variable has N^2 possible regimes; in the latter case, the aggregate variable is a 2-state variable.

We are interested in an intermediate model which simultaneously limits the possible regimes to a tractable number, estimates a national regime, and allows some heterogeneity across cities. This framework can be obtained by assuming that a national regime—subject to some restrictions—exists, but that departures from this national regime (i.e., idiosyncratic contractions) must be relatively pervasive (i.e., experienced by a group of cities). Thus, our model has both national cycles and periods during which groups of cities have contractions by themselves. Let κ represent the number of (possibly overlapping) groups of cities; the aggregate Markov variable has $K = \kappa + 2$ regimes (one for each idiosyncratic contraction, the national expansion, and the national contraction).[12]

3.1 Clustered Markov-switching

Formally, let $\mathbf{y}_t$ denote an $(N \times 1)$ vector of observed city-level building permit growth rates at date t and $\mathbf{Y}_t = (\mathbf{y}_t', \mathbf{y}_{t-1}', ..., \mathbf{y}_1')'$. Denote $\mathbf{S}_t$ as an $(N \times 1)$ vector of contraction indicators (so

of the counties in the 2009 definition of the MSA between 1970 and 1990. The share of manufacturing employment is computed from Census county-level data from County Business Patterns. Average winter temperature represents long-run typical temperatures obtained for each city. The unemployment rates were computed aggregating the number of the unemployed and the labor force at the county level with data from the Bureau of Labor Statistics, and subsequently averaging over the period 1988:1–2012:12. Housing density is total housing units in 1990 divided by the land area of the MSA. Loan volumes are aggregated from ZIP code level data on loan volumes from the Federal Reserve Bank of New York Equifax Consumer Credit Panel Data. *Subprime* loans are defined as those granted to individuals with an Equifax Risk Score of 660 or less. (This score is a internal generic risk score that ranges between 280 and 850.) Saiz's (2010) index of undevelopable land represents the proportion of area in each city that cannot be developed because of geographic constraints.

[12]The model is taken from Hamilton and Owyang (2012) and is also similar to Kaufmann (2010). These papers use clustering algorithms similar to Frühwirth-Schnatter and Kaufmann (2008) to reduce the dimension of the aggregate Markov-switching process. Other papers with multivariate Markov-switching models include Paap et al. (2009) and Leiva-Leon (2012).

$S_{nt} = 1$ when city n is in contraction and $S_{nt} = 0$ when city n is in expansion). Suppose that

$$\mathbf{y}_t = \mu_0 + \mu_1 \odot \mathbf{S}_t + \varepsilon_t, \tag{1}$$

where the nth element of the $(N \times 1)$ vector $\mu_0 + \mu_1$ is the average building permit growth in city n during contraction, the nth element of the $(N \times 1)$ vector μ_0 is the average building permit growth in city n during expansion, and $\odot$ is the Hadamard (element-by-element) product. For identification, we assume that $\mu_{0n} > 0$ and $\mu_{0n} + \mu_{1n} < 0$; that is, contractions are defined by strictly negative mean growth rates. Let $E(\varepsilon_t \varepsilon_t^{'}) = \mathbf{\Sigma}$, and we assume that the covariance matrix is diagonal with representative element σ_n^2. The diagonality restriction is made for parsimony and implies that the correlation across cities is driven primarily through simultaneity in their cycles.

We can summarize the individual S_{nt} with a scalar aggregate regime indicator Z_t that represents the time-t aggregate regime. Let $\mathbf{H}$ denote an $(N \times K)$ matrix whose elements are all zeros and ones and where K is the allowed number of possible aggregate permutations (regimes), including both idiosyncratic contractions and national expansion and contraction. The row n, column k element of $\mathbf{H}$ is 1 if city n is in a contraction when the aggregate regime is k. In a model in which all cities enter and exit contractions at the same time, $K = 2$, with the first column being all zeros and the second column is all ones. As an example, suppose that $K = 3$; this indicates three regimes: national-level expansion, national-level contraction, and one idiosyncratic contraction.

For exposition purposes only, consider the example of a cluster consisting of cities with manufacturing sectors larger than some predefined threshold. When $k = 1$, all cities are in expansion, by definition. When $k = 2$, all cities are in contraction, by definition. When $k = 3$, only the cities with manufacturing sectors above a certain threshold are in contraction; all other cities are in expansion. For purposes of this discussion, we refer to the regimes in which all cities move together as *national* regimes and refer to regimes in which some cities are in contraction but others are not as *idiosyncratic* contractions.[13]

The aggregate regime follows a polychotomous K-state Markov process with $(K \times K)$ transition kernel $\mathbf{P}$. In principle, we could model a world in which Z_t is allowed to transition to and from any aggregate regime. HO impose additional restrictions for identifying the clusters. They assume

[13] We do not refer to idiosyncratic *expansions* as these are simply idiosyncratic recessions for the complement set of states.

that the aggregate regime is free to transition to and from national-level expansions or contractions at any time. That is, if we label the first two regimes as national-level expansions or contractions, the first two rows and columns of $\mathbf{P}$ are unrestricted. However, HO impose the restriction that the aggregate regime cannot transition from one idiosyncratic cluster contraction to another. That is, if $K = 4$ and $Z_{t-1} = 4$, Z_t can take on only values of 1, 2, or 4. This aspect presents as zero restrictions on the transition kernel $\mathbf{P}$ and is described in more detail in the estimation section below.

The model can alternatively be depicted as a mixture of distributions for the mean growth rate of permits. The distribution of the growth rate of permits conditional on being in (aggregate) regime k is

$$\mathbf{y}_t | z_t = k \sim N(\mathbf{m}_k, \mathbf{\Sigma}),$$

where

$$\mathbf{m}_k = \mu_0 + \mu_1 \odot \mathbf{h}_k$$

for $\mathbf{h}_k$, the kth column of $\mathbf{H}$. It is important to note here that our setup allows cities to belong to more than one cluster. One could impose that cities belong to only one cluster, but given the variation that we observe in the data, we felt this was overly restrictive. The advantage of allowing membership in only one cluster is that cities would form unique *regions* but the restriction would also likely require a larger number of clusters.[14]

One might wonder what the advantage of using the clustered panel approach is compared with estimating each city separately. In the univariate Markov switching model, the posterior regime probability tends to identify a recession whenever the growth rate begins to turn negative. Thus, the model can pick up very short-lived, idiosyncratic negative growth periods. When the data are noisy, this sensitivity can lead to a large number of turning-points. In the panel, we require a significant number of cities in the cluster to exhibit negative growth rates before the algorithm identifies a turning point. Thus, our cluster recessions will tend to be less idiosyncratic than those identified by a collection of univariate Markov switching models.

[14] In our framework, the regions would not necessarily be geographic but would depend on the cyclical similarity of the member cities.

3.2 Logistic Clustering

One of the main features of the model is that it can be used to explain why cities' housing cycle experiences are correlated. To do this, we can model the cluster indicators h_{nk} as functions of a vector of fixed city-level covariates $\mathbf{x}_{nk}$ that influences whether city n is in a contraction when $Z_t = k$. Following Frühwirth-Schnatter and Kaufmann (2008) and HO, we assume that the probability that a city is in cluster k is defined by:

$$p(h_{nk}) = \begin{cases} \frac{1}{1+\exp\left(\mathbf{x}'_{nk}\beta_k\right)} & \text{if } h_{nk} = 0 \\ \frac{\exp\left(\mathbf{x}'_{nk}\beta_k\right)}{1+\exp\left(\mathbf{x}'_{nk}\beta_k\right)} & \text{if } h_{nk} = 1 \end{cases} \tag{2}$$

for $n = 1, ..., N$; $k = 1, ..., \kappa$. Note that (2) resembles the probability that we would obtain from a logistic regression model.

For implementation, we consider $p(h_{nk})$ as the prior probability that city n belongs to cluster k conditional only on the observed covariates. The business cycle data in conjunction with the prior probability will determine the posterior probability through an application of Bayes' rule. As explained in HO, we can take the βs as population parameters even though $p(h_{nk})$ represents a form of the prior probability. We can estimate the βs as we would other model parameters and they will determine which and to what extent the covariates are important for clustering.

4 Estimation

The model presented above is straightforward to estimate in a Bayesian environment. Given a prior, the joint posterior of the model parameters including the regimes can be generated by the Gibbs sampler (see Gelfand and Smith, 1990; Casella and George, 1992; Carter and Kohn, 1994). The Gibbs sampler iterates over draws from each parameter's conditional posterior distribution. After discarding a number of initial draws to achieve convergence, the remaining draws form the full joint posterior distribution of all of the model parameters.

Let Θ represent the full set of parameters. Then, Θ includes the regime growth rates, μ_0 and μ_1; the covariance matrix, $\mathbf{\Sigma}$; the transition probabilities, $\mathbf{P}$; the time series of aggregate regimes, $\mathbf{Z_T}$; the matrix defining the clusters $\mathbf{H}$; and the logistic parameters, β, ψ, and ξ. The number of clusters, κ, is assumed to be fixed to estimate the other model parameters and is discussed further below. For now, we will assume that the number of clusters κ is determined exogenously and is suppressed in the notation. There are four blocks of parameters to be sampled: each city's parameter set, $\theta_n = \left(\mu_{0n}, \mu_{1n}, \sigma_n^2\right)$; the aggregate business cycle, $\mathbf{Z_T}$, and its associated transition matrix, $\mathbf{P}$; the matrix $\mathbf{H}$ determining the cluster membership; and the logistic parameters, β, ψ, and ξ.

4.1 Priors

The Bayesian environment requires a set of prior distributions for the model parameters. The distributional assumptions for the priors will, in turn, yield distributional assumptions on the posteriors. The city cycle parameters θ_n are assumed to have a normal-inverse Gamma prior distribution. The transition probabilities for the aggregate regime process are assumed to have a Dirichlet prior distribution given the fixed number of regimes. The cluster indicators have the logistic prior discussed above with population parameters β that are normal. Prior hyperparameters are shown in Table 2.

4.2 Posterior Inference

As we noted above, the Gibbs sampler consists of iterative draws from the conditional distributions of the model parameters. In this subsection, we describe the draws; details for the sampler's posterior distributions can be found in HO.

Conditional on the other model parameters, the set of city-level parameters, θ, are conjugate normal-inverse Gamma and independent for all n. Thus, for each n, we first draw the μ_{0n} and μ_{1n} from a normal posterior distribution that depends in part on the regime-dependent conditional mean. We then draw the σ_n^{-2} from a Gamma posterior distribution. These draws can be made independently because the ε_{nt}s are assumed to be uncorrelated.

Conditional on the other model parameters, the posterior distribution of $\mathbf{Z_T}$ can be obtained from a multi-regime extension of the Hamilton (1989) filter, a discrete-state modification of the familiar Kalman filter. For the sampler, we compute the posterior regime probabilities for each time period and draw each Z_t recursively, starting with Z_T. This draw is described in Kim and Nelson (1999). Once we have obtained the regimes, we can compute the posterior distributions for probabilities in the transition kernel. These are conjugate Dirichlet distributions (the multiple regime equivalent to the beta distribution) and depend on the observed number of transitions from one regime to another. Because we are restricting the number of transitions between idiosyncratic contractions to zero, the posterior distribution for these transition probabilities will also be identically zero.

The cluster indicators can be drawn by an application of Bayes' rule. We draw the value of the cluster membership indicator for each city-cluster combination conditional on the memberships of all of the other cities. The posterior probability is influenced by the logistic prior probability (i.e., the covariates and the estimated βs) and the similarities of city n's housing cycle to the cycles of the cities in the cluster in question. Because we allow a city to have membership in multiple clusters, we must draw a separate indicator for each city-cluster combination.

The logistic prior parameters are drawn in three steps. The marginal inclusion coefficient, β_{nk}, is drawn from a conjugate normal. The logistic prior requires two other parameters: a latent logistic variable, ξ_{nk}, whose sign is determined by the value of h_{nk} and the variance of this variable, λ_{nk}. We follow Holmes and Held (2006) who generate ξ_{nk} from a truncated logistic and then generate λ_{nk} conditional on ξ_{nk}.

4.3 Choosing the Number of Clusters

The model outlined in Section 3 is defined for a fixed number of clusters, K. HO use techniques outlined in Chib (1995) and Chib and Jeliazkov (2001) to compute marginal likelihoods to determine K. These methods use resampling techniques to compute the posterior ordinate – a component of the marginal likelihood – and are accurate when computed with a large number of post-convergence iterations. While simple to code, the methods of Chib (1995) and Chib and Jeliazkov (2001) use Monte Carlo integration to compute the posterior ordinate and are computationally intensive when the model has a large number of parameter blocks. The number of clusters is then chosen as the model yielding the highest marginal likelihood which must be computed for each possible value of K. Because HO considered states, the number of clusters was assumed to be small and only a small number of marginal likelihoods were required to determine K.

In the present analysis, we have a large number of cities, which would require a larger number of marginal likelihood computations. Because the methods used to compute the marginal likelihoods are time consuming, we opted instead for computing a modified version of the BIC for each K for a number of clusters between 3 and 9. Computing the BIC has been shown to approximate the marginal likelihood (e.g., Kass and Raftery (1995) and Raftery (1995)) and is faster to compute because it does not require resampling. The modification attaches a prior to the model dimension, putting more weight on parsimonious models. We thus compute the average of the BICs computed at each draw of the Gibbs sampler. We then select the number of clusters that minimizes this measure, which in our results corresponds to $\kappa = 4$ and $K = 6$.

5 Results

The results of the estimation are comprised of the growth rates and variances of permits for each city, the regime processes for the nation and the subgroupings, and the cluster compositions.

5.1 Growth Rates

The model posits that the growth rate in city-level permits take on two average values over the housing cycle. During expansions, the mean growth rate is μ_0; during contractions, the mean growth rate falls to $\mu_0 + \mu_1$, since $\mu_1 < 0$. Table 3 lists the cities with the highest and lowest average expansion growth rates; Table 4 lists the cities with the highest and lowest average contraction growth rates, and Table 5 lists the cities with the highest and lowest variances. Figure 2 maps the means of μ_0, $\mu_0 + \mu_1$, and σ^2 for each of the cities in our sample.[15]

While there are large differences in the means across cities, there are surprisingly few geographic patterns. A number of cities in Texas, for example, have high expansion growth rates but also have large negative contraction growth rates. However, these combinations are not limited to Texas—or even warm or southern cities. Some cities in upstate New York, for example, experience similarly large expansion growth rates. Cities that have high expansion rates appear to be correlated with cities that have large negative contraction rates: the correlation between μ_0 and $\mu_0 + \mu_1$ is 35.4 percent.

Perhaps not surprisingly, cities with high growth rates also typically have a higher conditional variance; the correlation between μ_0 and σ^2 is 44.8 percent. Because the model restricts the cycle

[15]Table 8 shows the mean growth rates and the city-level variances for all of the 135 cities in our sample and includes the mean and sample standard deviation of each city's raw building permits growth series.

processes to achieve parsimony, idiosyncratic city-level fluctuations will manifest in the residuals. This result then suggests that cities with a rapidly growing housing stock are likely to also experience large, cycle-independent fluctuations.

5.2 National Housing Cycles

One of the main features of the HO model is that it estimates a pervasive national cycle, which affects—by assumption—all of the cities simultaneously. Because of the restriction that the national cycle includes all cities, one believing in abundant city-level heterogeneity might imagine that there would not be much of a national cycle. On the other hand, one believing in pervasive cross-city linkages might imagine that idiosyncratic cycles would be less common.

Figure 3 plots the posterior probabilities of a *national*-level housing contraction, $\Pr[Z_t = 2|\mathbf{Y}_T]$. The probabilities reflect the uncertainty around the polychotomous outcomes: a national housing expansion, a national contraction, or one of the κ cluster contractions. We note a few key features of the national housing contractions. First, the nation experiences two major housing downturns. The first downturn is around the time of the 1991 NBER recession and the second is around the time of the 2007-2009 NBER recession; the housing contraction lasts a little longer than the business cycle contraction in both cases. This timing is not surprising for the 2007-2009 episode, as it was an economic downturn specifically associated with a decline in the housing market.

Second, national housing contractions are identified with little uncertainty—that is, there are very few periods for which the regime probability is between zero and one. Third, a few short-lived instances national housing contractions are not associated with national recessions.

Finally, a national housing contraction does not occur during the 2001 NBER recession in our sample. This divergence in cycles is likely because there were localized housing downturns during these periods but they were not pervasive enough to include all of the cities in our sample. Thus, they can be characterized by cluster contractions instead of national contractions.[16]

[16]Indeed, this period is identified as a national housing contraction in models with a smaller the number of clusters. However, as we will see below, the data prefer a model with a larger number of idiosyncratic clusters. This finding is consistent with a large but not full set of cities experiencing a housing downturn in 2001.

5.3 City-level Housing Cycles

Before we can compare the city-level cycles, we must first determine the number of clusters preferred by the data. We treat the number of clusters as a model selection problem and compute a modified Bayesian information criterion (BIC) for various numbers of clusters. Our objective is to be as parsimonious as possible, so the parameter penalty in the BIC helps reduce the chance that the model becomes overparameterized.

We choose the model with $\kappa = 4$. It is important to note that our method does not create 4 mutually-exclusive housing regions. Because we allow cities to belong to multiple regions (or none at all), two cities both belonging to the same cluster will not necessarily have identical housing cycles.

Once we have determined the number of city-level idiosyncratic cycles, we can examine how the aggregate regime process evolves. Recall that, while we have defined the *national cycles* as the regimes for which all cities are either in or out of housing contractions, there will still be idiosyncratic contractions for some cities that are realized when the aggregate regime is $Z_t = k \geq 3$. Recall also that we have imposed the identifying restriction that disables transitions between these idiosyncratic contractions. Thus, the (aggregate) economy must pass through either full expansion or full contraction before transitioning into another idiosyncratic contraction.

Table 6 shows the estimated transition probabilities for the aggregate regime, Z_t. Bold zeros reflect the imposed restriction that Z_t cannot transition from one idiosyncratic regime to another. In addition to the imposed restrictions, we find that a few other transition probabilities are estimated to be zero. For example, we find no transitions from $Z_t = 1$ to $Z_{t+1} = 2$. How can this occur? The data indicate that transitions from national expansions to national contractions can only occur through one of the cluster contractions—that is, a group of cities always begins contracting before it spreads to the entire country.

Figure 4 plots the posterior probabilities of the idiosyncratic clusters, $\Pr[Z_t = k + 2|\Omega_T]$. We also plot the probability of the national contraction in each panel for reference. The clusters can take a number of forms; these include (i) cities that experience idiosyncratic contractions; (ii) cities that stay in contraction after the nation exits; and (iii) cities that begin to contract before the nation. The first type of cluster consists of cities that experience housing contractions unrelated to the national cycle, e.g., Clusters 1 and 2. Clusters 3 and 4 appear to be characterized by the third type. Both of these groups of cities begin contracting before the national contraction are always followed by a national contraction. In this case, we find no evidence of the second type of cluster for housing cycles.

Figure 5 in panels (a) through (d) shows the posterior cluster membership probabilities. In these maps, we display each city's posterior probability of membership in each particular cluster. As with the growth rates, we find only loose geographic patterns in the behavior of the city housing cycles.

Cluster 1 contains cities all across the country without an obvious geographical or industrial pattern, although primarily in the Midwest, South, and the East Coast, excluding larger cities such as Chicago, New York, and Atlanta. The predominant feature of these cities' housing experiences is that they all contracted in the mid 1990s and early 2000s while the rest of the nation expanded.

Cluster 2 is also composed of cities that have idiosyncratic contractions but has a much smaller membership. Again, there is no real geographic pattern to membership. Neighboring cities (e.g., Youngstown is in but Cleveland is out; Tulsa is out but Oklahoma City is in) do not appear to influence each other's membership in this cluster. These cities have a large number of short, idiosyncratic contractions mostly in the mid 1990s and prior to the beginning of the national contraction that preceded the Great Recession.

Cluster 3 does, to some extent, exhibit a more geographical pattern with cities along the East Coast and in the South appearing to be more likely to be included. This cluster led the two national downturns that were associated with the two NBER recessions in our sample. These results suggest that national downturns begin in a large number of cities and eventually grow to affect all cities (i.e., a transition from expansion to a Cluster 3 contraction to a national contraction).

Finally, the final panel of Figure 5 shows that Cluster 4 is another large group, containing cities in California, New England, Arizona, Texas, the South, and the Midwest. This cluster precedes the final national contraction in our sample, which occurs a few years subsequent to the contraction associated with the Great Recession. It appears that the Great Recession's affect on housing persisted beyond the economic contraction but the effect was less pervasive. Some cities (those excluded from Cluster 4) experienced a brief rebound before another short national contraction.

In general, we conclude that geography and size (population) do not appear to be the only key determinants of cluster composition. The larger clusters might appear regionally connected but they are so large as to obscure any real patterns. In the next section, we formally investigate what factors might determine cluster membership.

5.4 What Factors Affect the Comovements

To help determine the factors that might make city-level housing cycles comove, we included a set of city-level covariates in the prior for the clusters.[17] These variables are intended to characterize differences and similarities in the supply and demand for the cities' housing. Demand elements include population growth (which could reflect migration or immigration to/from the city), average winter temperature (which may suggest seasonal demand for housing), and the average unemployment rate. Housing density and the index of undevelopable land suggest how easily new housing can be constructed in the metro area. We also include covariates related to subprime mortgages, as an indicator of local financial conditions.

Table 7 shows the estimated values of the coefficients in the logistic prior, where bold indicates values for which zero lies outside the interior 95-percent coverage interval of the posterior distribution of the βs. We find that housing demand covariates play an important role for determining *most* of the clusters *(1, 2 and 4)*. In general, the supply of land does not appear to play an important role in synchronizing cities' housing cycles. This result does not suggest that these factors are not important for housing markets in general. They may play a role in determining similarities in the trends in housing markets and may be more important for prices than for permits.[18]

Cluster membership is mainly driven by variables coming from the demand side. This pattern is especially true for Clusters 1, 2, and 4. In particular, housing density, as measured by units per square kilometer, and average population growth both had a negative and significant effect on the probability of belonging to Cluster 1. Both demand-side and financial variables are important covariates for determining membership in Cluster 2. The change in the share of subprime mortgages has a positive and significant effect on the probability of being part of Cluster 2. Finally, housing

[17]The prior can be thought of as sorting a city into or out of a cluster when the cyclical data (the city's cycle compared to the cluster's cycle) is inconclusive. The effect of the prior, in a sense, is to sort the city into the cluster if the city has similar characteristics to the other cities in that cluster. The prior is only important if the likelihood of the being in or being out of the cluster are about equal.

[18]In fact, the elasticity of land supply plays an important role in determining the clusters when we use house price growth as indicators of housing cycles.

units per square kilometer has a significant and negative effect on Cluster 4 membership, suggesting that the cluster is composed of cities with lower housing density. Membership in Cluster 3, on the other hand, is driven by economic and geographic factors. In particular, Cluster 3 is characterized by warmer climates and lower cities with average unemployment rates.

We find that the determinants of housing cycle similarity differ substantially from the determinants of business cycle similarity, which supports Ghent and Owyang's (2010) conclusion that, at a subnational level, housing cycles and business cycles are not as connected as they appear to be at the national level. In general, we find that housing demand is the main determinant of similarities in the cyclical fluctuations in housing instead of housing supply. Perhaps this result is not surprising as housing supply would tend to change slowly compared to housing demand, and the cyclical features we emphasize in the model are measured at a medium frequency.

6 Conclusions

Despite the strong linkages often found between housing market cycles and business cycles at the national level, the relationship between housing and the business cycle is less clear when considering subnational data because housing markets are highly localized. In this paper, we examine the cross-city linkages in housing cycles by estimating a cluster Markov-switching model of building permits. We find that there does exist a national housing cycle which roughly coincides with the national business cycle as determined by the NBER. In addition, cities experience idiosyncratic housing contractions either through early entry into national contractions, prolonged exposure to national contractions, or purely idiosyncratic contractions.

We find that the presence of regional housing cycles may depend on local factors in addition to national factors. We estimate that idiosyncratic contractions occur in four clusters, for which membership is primarily influenced by similarities in factors influencing housing demand as opposed to factors influencing housing supply or factors influencing the similarity of business cycles. For the most part, we also find that geography does not seem to be an important determinant of cluster membership.

Finally, regional differences in housing cycles can have implications for the transmission of monetary policy or for implementing macroprudential policies across regions in the U.S. The possibility of different reactions to a single national-level policy suggests that models should take heterogeneity into account and consider, for example, differences in housing demand, the size of the population, or different strengths of housing shocks across regions when designing policy. In light of our results, housing demand heterogeneity could be an important consideration when assessing the relative effectiveness of a policy across multiple regions.

References

Bernanke, Ben S., "Housing, Mortgage Markets, and Foreclosures," December 2008, remarks delivered at *The Federal Reserve System Conference on Housing and Mortgage Markets.*

Brady, Ryan R., "Measuring the diffusion of housing prices across space and over time," *Journal of Applied Econometrics*, March 2011, *26*(2), pp. 213–231.

Brueckner, Jan K., "Urban sprawl: diagnosis and remedies," *International Regional Science Review*, April 2000, *23*(2), pp. 160–171.

Can, Ayse, "The measurement of neighbourhood dynamics in urban house prices," *Economic Geography*, July 1990, *66*(3), pp. 254–272.

Carlino, Gerald and Keith Sill, "Regional income fluctuations: common trends and common cycles," *Review of Economics and Statistics*, August 2001, *83*(3), pp. 446–456.

Carter, Christopher K. and Robert Kohn, "On gibbs sampling for state space models," *Biometrika*, August 1994, *81*(3), pp. 541–553.

Casella, George and Edward I. George, "Explaining the bibbs sampler," *American Statistician*, August 1992, *46*(3), pp. 167–174.

Chib, Siddhartha, "Marginal likelihood from the gibbs output," *Journal of the American Statistical Association*, December 1995, *90*(432), pp. 1313–1321.

Chib, Siddhartha and Ivan Jeliazkov, "Marginal likelihood from the metropolis-hastings output," *Journal of the American Statistical Association*, March 2001, *96*(453), pp. 270–281.

Clayton, Jim, Norman G. Miller and Liang Peng, "Price-volume correlation in the housing market: causality and co-movements," *Journal of Real Estate Finance and Economics*, 2010, *40*(1), pp. 14–40.

Cotter, John, Stuart Gabriel and Richard Roll, "Can metropolitan housing risk be diversified? A cautionary tale from the recent boom and bust," Technical report, UCD Geary Institute, 2012.

Couch, Chris and Jay Karecha, "Controlling urban sprawl: some experiences from Liverpool," *Cities*, October 2006, *23* (5), pp. 353–363.

Davis, Morris A. and Jonathan Heathcote, "Housing and the business cycle," *International Economic Review*, August 2005, *46* (3), pp. 751–784.

Del Negro, Marco and Christopher Otrok, "99 Luftballons: monetary policy and the house price boom across U.S. states," *Journal of Monetary Economics*, October 2007, *54* (7), pp. 1962–1985.

Frühwirth-Schnatter, Sylvia and Sylvia Kaufmann, "Model-based clustering of multiple times series," *Journal of Business and Economic Statistics*, January 2008, *26* (1), pp. 78–89.

Füss, Roland, Joachim Zietz and Bing Zhu, "Why do local housing prices react so differently to a monetary stimulus?" Technical report, University of St. Gallen, 2012.

Gelfand, Alan E. and Adrian F. M. Smith, "Sampling-based approaches to calculating marginal densities," *Journal of the American Statistical Association*, June 1990, *85* (410), pp. 398–409.

Ghent, Andra C. and Michael T. Owyang, "Is housing the business cycle? evidence from U.S. cities," *Journal of Urban Economics*, May 2010, *67* (3), pp. 336–351.

Glaeser, Edward L., Joseph Gyourko, Eduardo Morales and Charles G. Nathanson, "Housing dynamics," May 2011, unpublished Manuscript.

Hamilton, James D., "A new approach to the economic analysis of nonstationary time series and the business cycle," *Econometrica*, March 1989, *57* (2), pp. 357–384.

Hamilton, James D. and Michael T. Owyang, "The propagation of regional recessions," *Review of Economics and Statistics*, December 2012, *94* (4), pp. 935–947.

Holly, Sean, Hashem M. Pesaran and Takashi Yamagata, "The temporal and spatial diffusion of house prices in the UK," *Journal of Urban Economics*, 2011, *69* (1), pp. 2–23.

Holmes, Chris C. and Leonhard Held, "Bayesian auxiliary variable models for binary and multinomial regression," *Bayesian Analysis*, 2006, *1* (1), pp. 145–168.

Iacoviello, Matteo, “House prices, borrowing constraints, and monetary policy in the business cycle,” *American Economic Review*, June 2005, *95* (3), pp. 739–764.

Iacoviello, Matteo and Stefano Neri, “Housing market spillovers: evidence from an estimated DSGE model,” *American Economic Journal: Macroeconomics*, April 2010, *2* (2), pp. 125–64.

Ioannides, Yannis M. and Jeffrey E. Zabel, “Neighborhood effects and housing demand,” *Journal of Applied Econometrics*, 2003, *18*, pp. 563–584.

Kallberg, Jarl G., Crocker H. Liu and Paolo Pasquariello, “On the price comovement of U.S. residential real estate markets,” *Real Estate Economics*, 2014, *42* (1), pp. 71–108.

Kass, Robert E. and Adrian E. Raftery, “Bayes factors,” *Journal of the American Statistical Association*, June 1995, *90* (430), pp. 773–795.

Kaufmann, Sylvia, “Dating and forecasting turning points by Bayesian clustering with dynamic structure: a suggestion with an application to Austrian data,” *Journal of Applied Econometrics*, March 2010, *25* (2), pp. 309–344.

Kim, Chang-Jin and Charles R. Nelson, *State-space models with regime switching*, The MIT Press, Cambridge, MA, 1999.

Landier, Augustin, David Sraer and David Thesmar, “Banking deregulation and the rise in house price comovement,” Technical report, 2013.

Leamer, Edward E., “Housing is the business cycle,” Working Paper 13428, NBER, September 2007.

Leiva-Leon, Danilo, “Monitoring synchronization of regional recessions: a markov-switching network approach,” October 2012, unpublished manuscript.

Meen, Geoffrey, “Regional house prices and the ripple effect: a new interpretation,” *Housing Studies*, 1999, *14* (6), pp. 733–753.

Moench, Emanuel and Serena Ng, “A hierarchical factor analysis of U.S. housing market dynamics,” *The Econometrics Journal*, February 2011, *14* (1), pp. C1–C24.

Oikarinen, Elias, "Price linkages between stock, bond and housing markets-evidence from Finnish data," Technical Report 1004, Keskusteluaiheita Discussion papers, 2006.

O'Sullivan, Arthur, *Urban economics*, McGraw Hill, New York, NY, 2009.

Owyang, Michael T., Jeremy Piger, and Howard J. Wall, "Business cycle phases in U.S. states," *Review of Economics and Statistics*, December 2005, *87* (4), pp. 604–616.

Owyang, Michael T., Jeremy M. Piger, Howard J. Wall and Christopher H. Wheeler, "The economic performance of cities: a markov-switching approach," *Journal of Urban Economics*, December 2008, *64* (3), pp. 538–550.

Paap, Richard, Rene Segers and Dick van Dijk, "Do leading indicators lead peaks more than troughs?" *Journal of Business and Economic Statistics*, January 2009, *27* (4), pp. 528–543.

Pollakowski, Henry O. and Traci S. Ray, "Housing price diffusion patterns at different aggregation levels: an examination of housing market efficiency," *Journal of Housing Research*, 1997, *8* (1), pp. 107–124.

Raftery, Adrian E., "Bayesian model selection in social research," *Sociological Methodolgy*, 1995, *25*, pp. 111–163.

Saiz, Albert, "The geographic determinants of housing supply," *The Quarterly Journal of Economics*, August 2010, *125* (3), pp. 1253–1296.

Stevenson, Simon, "House price diffusion and inter-regional and cross-border house price dynamics," *Journal of Property Research*, August 2004, *21*, pp. 301–320.

Stock, James H. and Mark W. Watson, *The evolution of national and regional factors in U.S. housing construction*, Oxford University Press. Tim Bollerslev and Jeffrey Russell and Mark Watson. Volatility and Time Series Econometrics: Essays in Honour of Robert F. Engle, Oxford, 2010.

Table 1: Covariates Summary Statistics

Covariate	**Mean**	**SD**	**Median**	**Min**	**Max**
Housing units per sq. km. 1990	56.5	53.2	39.7	4.1	380.7
Avg. population growth (%) 1970–1990	1.5	1.3	1.2	-0.6	6.0
Manufacturing employment share (%) 1990	21.3	8.5	20.0	3.2	58.5
Average winter temperature (° Celsius)	4.3	6.9	3.1	-9.6	19.6
Average unemployment rate (%) 1988–2012	6.0	1.8	5.6	3.3	14.2
Saiz's (2010) index of undevelopable land (%)	27.1	21.0	21.9	0.9	79.6
Saiz's (2010) elasticity of land supply	2.1	1.0	1.8	0.7	5.5
Change in share of subprime mortgages 2002-2005	-1.5	8.3	-1.9	-36.8	44.1
Growth in subprime mortgages 2002-2005	11.5	12.0	11.6	-20.3	50.4

Notes:
MSA population, housing units, and land area were aggregated from county-level data from the Census Bureau to match 2009 MSA definitions available at `http://www.census.gov/population/metro/files/lists/2009/List4.txt` (Retrieved on 11 April 2013).
The manufacturing employment share was computed as the ratio of MSA manufacturing employment to total employment, aggregating county-level data from the 1990 County Business Patterns from the Census Bureau.
Average winter temperatures represent long-run typical temperatures obtained for each city from the Department of Energy.
Unemployment rates were computed aggregating the number of the unemployed and the labor force at the county level with data from the Bureau of Labor Statistics, and subsequently were averaged over the period 1988:1–2012:12.
Saiz's (2010) index represents the percent of area in each city that cannot be developed because of geographic constraints, and was graciously provided by the author.
The change in the proportion of subprime mortgage loans and the growth in mortgage loan balances were obtained from credit bureau data at the zip code level aggregated at the metropolitan area.

Table 2: Priors for Estimation

Parameter	Prior Distribution	Hyperparameters	
$[\mu_{0n}, \mu_{1n}]'$	$N\left(\mathbf{m}, \sigma^2\mathbf{M}\right)$	$\mathbf{m} = [2, -1]'\ ;\ \mathbf{M} = \mathbf{I}_2$	$\forall n$
σ_n^{-2}	$\Gamma\left(\frac{\nu}{2}, \frac{\delta}{2}\right)$	$\nu = 2\ ;\ \delta = 2$	$\forall n$
$\mathbf{P}$	$\mathbf{D}\left(\alpha\right)$	$\alpha_i = 0$	$\forall i$
β_k	$N\left(\mathbf{b}, \mathbf{B}\right)$	$\mathbf{b} = \mathbf{0}_p\ ;\ \mathbf{B} = \frac{1}{2}\mathbf{I}_p$	$\forall k$

Notes:
The table shows the prior distributions and their hyperparameters for all model parameters.
$D(\cdot)$ is the Dirichlet distribution.

Table 3: Highest and Lowest Permit Growth Rates: Expansion

Cities with lowest μ_0		
CBSA	MSA	μ_0
17460	Cleveland-Elyria-Mentor, OH	0.043
40380	Rochester, NY	0.046
39300	Providence-New Bedford-Fall River, RI-MA	0.047
33340	Milwaukee-Waukesha-West Allis, WI	0.047
25860	Hickory-Lenoir-Morganton, NC	0.049
28940	Knoxville, TN	0.055
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.064
35300	New Haven-Milford, CT	0.073
44140	Springfield, MA	0.074
10420	Akron, OH	0.074
Cities with highest μ_0		
CBSA	MSA	μ_0
14260	Boise City-Nampa, ID	0.283
18580	Corpus Christi, TX	0.283
21500	Erie, PA	0.293
41700	San Antonio-New Braunfels, TX	0.294
19780	Des Moines-West Des Moines, IA	0.298
12940	Baton Rouge, LA	0.311
13140	Beaumont-Port Arthur, TX	0.333
12420	Austin-Round Rock-San Marcos, TX	0.390
28660	Killeen-Temple-Fort Hood, TX	0.449
41940	San Jose-Sunnyvale-Santa Clara, CA	0.463

Notes:
The table shows the cities with the lowest (top panel) and highest (bottom panel) growth rates in permits during expansion (μ_0).
CBSA is the city's Core-Based Statistical Area code.
Growth rates are the average year-over-year changes given in decimal points (0.01 is one percent).

Table 4: Highest and Lowest Permit Growth Rates: Recession

Cities with lowest $\mu_0 + \mu_1$		
CBSA	MSA	$\mu_0 + \mu_1$
15980	Cape Coral-Fort Myers, FL	−0.455
33700	Modesto, CA	−0.450
39900	Reno-Sparks, NV	−0.449
38940	Port St. Lucie, FL	−0.427
19820	Detroit-Warren-Livonia, MI	−0.410
16980	Chicago-Joliet-Naperville, IL-IN-WI	−0.407
33100	Miami-Fort Lauderdale-Pompano Beach, FL	−0.397
44700	Stockton, CA	−0.390
40140	Riverside-San Bernardino-Ontario, CA	−0.379
12060	Atlanta-Sandy Springs-Marietta, GA	−0.371
Cities with highest $\mu_0 + \mu_1$		
CBSA	MSA	$\mu_0 + \mu_1$
36540	Omaha-Council Bluffs, NE-IA	−0.059
12420	Austin-Round Rock-San Marcos, TX	−0.053
21500	Erie, PA	−0.051
21340	El Paso, TX	−0.032
16620	Charleston, WV	−0.023
30780	Little Rock-North Little Rock-Conway, AR	−0.023
22180	Fayetteville, NC	−0.016
33660	Mobile, AL	0.022
35380	New Orleans-Metairie-Kenner, LA	0.088
13140	Beaumont-Port Arthur, TX	0.131

Notes:
The table shows the cities with the lowest (top panel) and highest (bottom panel) growth rates in permits during recession ($\mu_0 + \mu_1$).
CBSA is the city's Core-Based Statistical Area code.
Growth rates are the average year-over-year changes given in decimal points (0.01 is one percent).

Table 5: Highest and Lowest Permit Volatility

Cities with lowest σ^2		
CBSA	MSA	σ^2
41180	St. Louis, MO-IL	0.082
17140	Cincinnati-Middletown, OH-KY-IN	0.084
16980	Chicago-Joliet-Naperville, IL-IN-WI	0.089
17460	Cleveland-Elyria-Mentor, OH	0.090
39300	Providence-New Bedford-Fall River, RI-MA	0.092
38300	Pittsburgh, PA	0.094
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	0.095
16860	Chattanooga, TN-GA	0.106
33460	Minneapolis-St. Paul-Bloomington, MN-WI	0.108
12060	Atlanta-Sandy Springs-Marietta, GA	0.109
Cities with highest σ^2		
CBSA	MSA	σ^2
16620	Charleston, WV	0.429
28660	Killeen-Temple-Fort Hood, TX	0.437
22180	Fayetteville, NC	0.437
44060	Spokane, WA	0.485
21500	Erie, PA	0.486
46700	Vallejo-Fairfield, CA	0.599
13140	Beaumont-Port Arthur, TX	0.666
41500	Salinas, CA	0.689
41940	San Jose-Sunnyvale-Santa Clara, CA	1.095
28940	Knoxville, TN	1.394

Notes:
The table shows the cities with the lowest (top panel) and highest (bottom panel) residual volatility in permits (σ^2).
CBSA is the city's Core-Based Statistical Area code.

Table 6: Transition Probabilities. Permits

		To Exp	**To Rec**	**To C1**	**To C2**	**To C3**	**To C4**
		$Z_{t-1} = 1$	$Z_{t+1} = 2$	$Z_{t+1} = 3$	$Z_{t+1} = 4$	$Z_{t+1} = 5$	$Z_{t+1} = 6$
From Exp	$Z_t = 1$	0.88	0	0.02	0.08	0.02	0.01
From Rec	$Z_t = 2$	0.07	0.93	0	0	0	0
From C1	$Z_t = 3$	0.12	0	0.88	**0**	**0**	**0**
From C2	$Z_t = 4$	0.32	0	**0**	0.68	**0**	**0**
From C3	$Z_t = 5$	0	0.14	**0**	**0**	0.86	**0**
From C4	$Z_t = 6$	0	0.11	**0**	**0**	**0**	0.89

Notes:
The table shows the transition probabilities ($\mathbf{P}$) for the aggregate state variable (Z_t) for $K = 4$ clusters.
Exp and **Rec** signify national contractions.
C1 through **C4** signify the corresponding cluster contraction.
Bolded zeros represent ex ante identifying restrictions on the probabilities.

Table 7: Explaining Housing Clusters: Permits

Covariate	β_1	β_2	β_3	β_4
Constant	0.415	**-1.168**	**0.566**	0.713
Housing units per sq. km. 1990	**-0.158**	-0.113	0.067	**-0.343**
Avg. population growth (%) 1970–1990	**-0.313**	**-0.238**	-0.074	-0.046
Manufacturing employment share (%) 1990	0.037	0.040	0.005	0.042
Average winter temperature (° Celsius)	0.144	0.029	**0.213**	0.113
Average unemployment rate (%) 1988–2012	-0.154	0.023	**-0.317**	-0.014
Saiz's (2010) index of undevelopable land (%)	0.051	0.031	-0.080	0.026
Saiz's (2010) elasticity of land supply	0.085	0.042	-0.099	0.151
Change in share of subprime mortgages 2002-2005	0.051	**0.172**	0.046	0.055
Growth in subprime mortgages 2002-2005	-0.048	0.012	0.017	0.033

Notes:
Coefficients other than the constant, c, have been scaled by $\Lambda(c)(1-\Lambda(c))$, where $\Lambda(x) = (1+\exp(-x))^{-1}$ is the logistic *cdf*. Because the covariates have been standardized to have mean zero and unit standard deviation, the scaled coefficients can be interpreted as marginal effects evaluated at the means, and represent the change in the likelihood of cluster membership in response to a one-standard-deviation from the mean in the variable of interest.
Coefficients in bold indicate that zero lies outside the interior 95 percent coverage interval.

Table 8: List of Cities and Permits Growth Rate Statistics

		Permits Growth Rate (%)	
CBSA	MSA	Mean	SD
10420	Akron, OH	-3.5	35.0
10580	Albany-Schenectady-Troy, NY	1.7	45.0
10740	Albuquerque, NM	4.9	42.9
10900	Allentown-Bethlehem-Easton, PA-NJ	1.1	36.9
11460	Ann Arbor, MI	0.7	75.6
11700	Asheville, NC	3.6	41.7
12060	Atlanta-Sandy Springs-Marietta, GA	2.4	35.7
12260	Augusta-Richmond County, GA-SC	5.2	40.6
12420	Austin-Round Rock-San Marcos, TX	23.7	67.3
12540	Bakersfield-Delano, CA	3.3	48.0
12580	Baltimore-Towson, MD	0.9	38.4
12940	Baton Rouge, LA	15.2	65.0
13140	Beaumont-Port Arthur, TX	27.2	88.9
13820	Birmingham-Hoover, AL	8.4	46.8
14260	Boise City-Nampa, ID	12.8	47.4
14460	Boston-Cambridge-Quincy, MA-NH	2.8	34.5
14860	Bridgeport-Stamford-Norwalk, CT	7.5	55.7
15180	Brownsville-Harlingen, TX	10.6	42.8
15940	Canton-Massillon, OH	2.5	41.5
15980	Cape Coral-Fort Myers, FL	7.0	47.6
16620	Charleston, WV	11.6	66.9
16700	Charleston-North Charleston-Summerville, SC	6.0	39.2
16740	Charlotte-Gastonia-Rock Hill, NC-SC	5.1	39.2
16860	Chattanooga, TN-GA	1.2	31.2
16980	Chicago-Joliet-Naperville, IL-IN-WI	-0.4	31.3
17140	Cincinnati-Middletown, OH-KY-IN	-1.9	27.1
17460	Cleveland-Elyria-Mentor, OH	-1.4	27.4
17820	Colorado Springs, CO	13.1	52.4
17900	Columbia, SC	6.3	38.8
17980	Columbus, GA-AL	3.9	51.6

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		Permits Growth Rate (%)	
CBSA	MSA	Mean	SD
18580	Corpus Christi, TX	14.0	62.7
19100	Dallas-Fort Worth-Arlington, TX	7.3	31.2
19340	Davenport-Moline-Rock Island, IA-IL	11.5	58.9
19380	Dayton, OH	5.3	56.0
19660	Deltona-Daytona Beach-Ormond Beach, FL	-0.7	40.0
19740	Denver-Aurora-Broomfield, CO	11.6	46.6
19780	Des Moines-West Des Moines, IA	15.7	63.1
19820	Detroit-Warren-Livonia, MI	1.7	38.6
20260	Duluth, MN-WI	8.1	53.3
20500	Durham-Chapel Hill, NC	12.1	60.5
21340	El Paso, TX	12.8	61.0
21500	Erie, PA	17.6	78.8
21660	Eugene-Springfield, OR	12.4	65.0
21780	Evansville, IN-KY	4.7	46.2
22180	Fayetteville, NC	18.3	68.5
23060	Fort Wayne, IN	1.9	37.6
23420	Fresno, CA	4.6	46.3
24340	Grand Rapids-Wyoming, MI	1.6	36.5
24660	Greensboro-High Point, NC	5.5	45.8
24860	Greenville-Mauldin-Easley, SC	5.9	37.8
25420	Harrisburg-Carlisle, PA	2.9	40.8
25540	Hartford-West Hartford-East Hartford, CT	-0.6	39.4
25860	Hickory-Lenoir-Morganton, NC	-0.5	38.3
26420	Houston-Sugar Land-Baytown, TX	12.6	36.9
26620	Huntsville, AL	6.7	52.4
26900	Indianapolis-Carmel, IN	2.4	31.1
27140	Jackson, MS	7.8	51.9
27260	Jacksonville, FL	5.1	42.1
28020	Kalamazoo-Portage, MI	9.3	62.0
28140	Kansas City, MO-KS	6.0	50.8
28660	Killeen-Temple-Fort Hood, TX	26.8	99.9
28700	Kingsport-Bristol-Bristol, TN-VA	4.4	41.7
28940	Knoxville, TN	-26.8	276.0

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		Permits Growth Rate (%)	
CBSA	MSA	Mean	SD
29460	Lakeland-Winter Haven, FL	7.5	51.7
29540	Lancaster, PA	4.6	48.8
29620	Lansing-East Lansing, MI	3.1	53.8
29820	Las Vegas-Paradise, NV	4.1	45.9
30460	Lexington-Fayette, KY	6.7	47.4
30780	Little Rock-North Little Rock-Conway, AR	13.3	56.2
31140	Louisville/Jefferson County, KY-IN	4.7	39.0
31540	Madison, WI	6.0	44.1
31700	Manchester-Nashua, NH	0.1	44.5
32580	McAllen-Edinburg-Mission, TX	11.7	43.9
32820	Memphis, TN-MS-AR	7.8	55.0
33100	Miami-Fort Lauderdale-Pompano Beach, FL	1.1	40.5
33340	Milwaukee-Waukesha-West Allis, WI	-1.2	35.7
33460	Minneapolis-St. Paul-Bloomington, MN-WI	2.2	36.3
33660	Mobile, AL	15.4	65.6
33700	Modesto, CA	1.5	60.7
33860	Montgomery, AL	7.5	65.0
34980	Nashville-Davidson–Murfreesboro–Franklin, TN	6.7	42.6
35300	New Haven-Milford, CT	-1.9	44.6
35380	New Orleans-Metairie-Kenner, LA	22.1	97.4
35620	New York-Northern New Jersey-Long Island, NY-NJ-PA	3.4	33.2
35980	Norwich-New London, CT	0.3	49.1
36260	Ogden-Clearfield, UT	6.5	37.1
36420	Oklahoma City, OK	9.9	42.2
36540	Omaha-Council Bluffs, NE-IA	7.5	43.7
36740	Orlando-Kissimmee-Sanford, FL	5.4	43.6
37100	Oxnard-Thousand Oaks-Ventura, CA	7.5	69.6
37340	Palm Bay-Melbourne-Titusville, FL	0.0	39.4
37860	Pensacola-Ferry Pass-Brent, FL	6.7	49.8
37900	Peoria, IL	9.6	58.2
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	-1.1	28.3
38060	Phoenix-Mesa-Glendale, AZ	4.8	37.4
38300	Pittsburgh, PA	1.2	28.9

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		Permits Growth Rate (%)	
CBSA	MSA	Mean	SD
38860	Portland-South Portland-Biddeford, ME	1.0	34.6
38940	Port St. Lucie, FL	1.1	52.4
39300	Providence-New Bedford-Fall River, RI-MA	-4.5	29.1
39340	Provo-Orem, UT	17.9	53.4
39740	Reading, PA	1.2	50.4
39900	Reno-Sparks, NV	11.1	66.0
40060	Richmond, VA	-0.4	33.7
40140	Riverside-San Bernardino-Ontario, CA	-1.3	37.6
40380	Rochester, NY	-2.3	35.5
40420	Rockford, IL	1.5	49.3
41180	St. Louis, MO-IL	-0.6	27.7
41420	Salem, OR	10.2	71.2
41500	Salinas, CA	13.2	90.5
41700	San Antonio-New Braunfels, TX	12.9	46.9
41740	San Diego-Carlsbad-San Marcos, CA	7.2	59.2
41860	San Francisco-Oakland-Fremont, CA	7.3	50.9
41940	San Jose-Sunnyvale-Santa Clara, CA	39.2	156.2
42220	Santa Rosa-Petaluma, CA	3.9	63.5
42340	Savannah, GA	8.3	51.9
42540	Scranton–Wilkes-Barre, PA	0.9	43.1
42660	Seattle-Tacoma-Bellevue, WA	3.9	36.7
43780	South Bend-Mishawaka, IN-MI	6.8	63.4
44060	Spokane, WA	13.2	71.1
44140	Springfield, MA	-3.3	37.8
44180	Springfield, MO	7.9	47.8
44700	Stockton, CA	2.8	48.1
45060	Syracuse, NY	4.5	55.5
45300	Tampa-St. Petersburg-Clearwater, FL	4.8	42.1
45780	Toledo, OH	4.1	52.5
46060	Tucson, AZ	8.2	53.3
46140	Tulsa, OK	8.8	41.5
46700	Vallejo-Fairfield, CA	18.3	93.1
47260	Virginia Beach-Norfolk-Newport News, VA-NC	-4.1	55.3

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		Permits Growth Rate (%)	
CBSA	MSA	Mean	SD
47300	Visalia-Porterville, CA	1.9	38.2
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	2.9	34.9
48620	Wichita, KS	3.7	41.3
49340	Worcester, MA	3.4	44.9
49620	York-Hanover, PA	-0.1	39.7
49660	Youngstown-Warren-Boardman, OH-PA	0.2	42.3

Figure 1: Building Permits. A Few Cities and the Nation

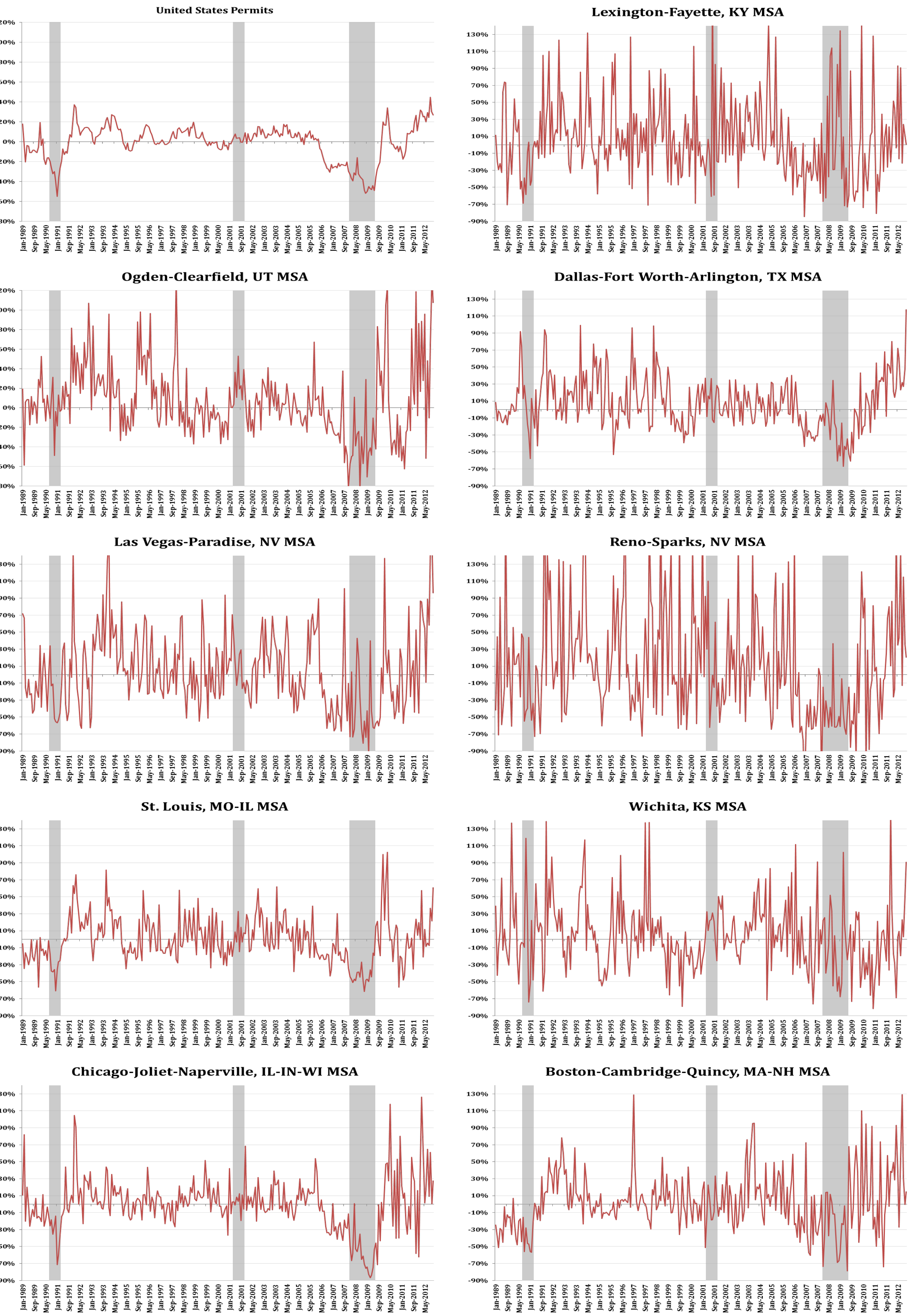
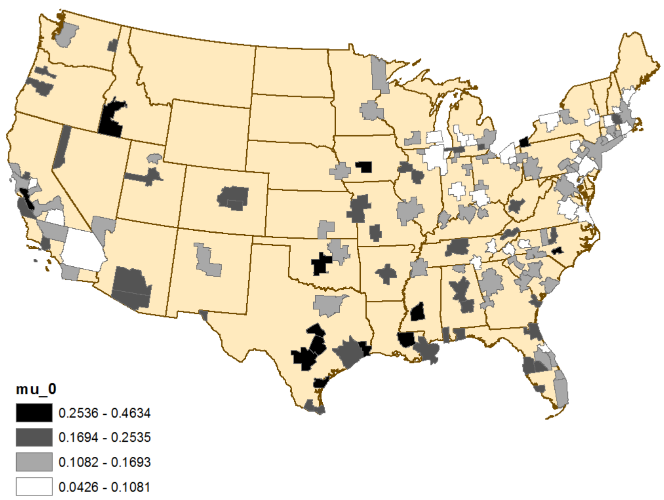
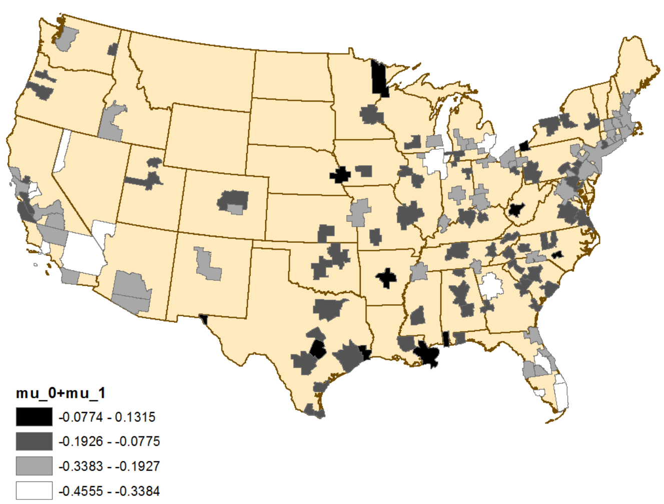


Figure 2: Model estimates

(a) μ_0



(b) $\mu_0 + \mu_1$



(c) σ^2

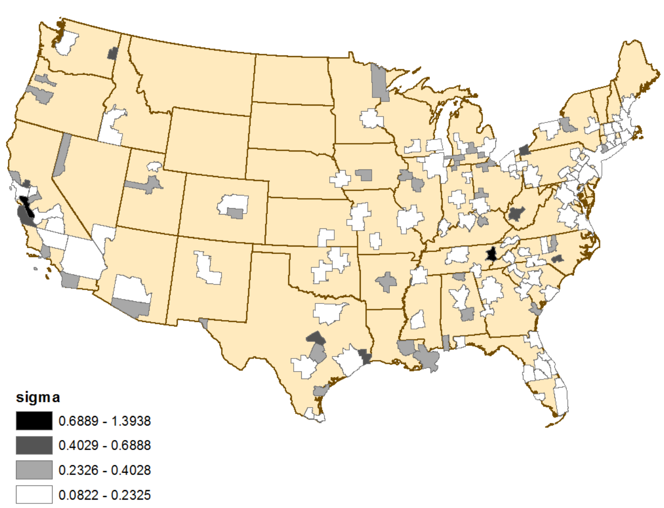


Figure 3: Posterior Probabilities of a National Level Housing Recession

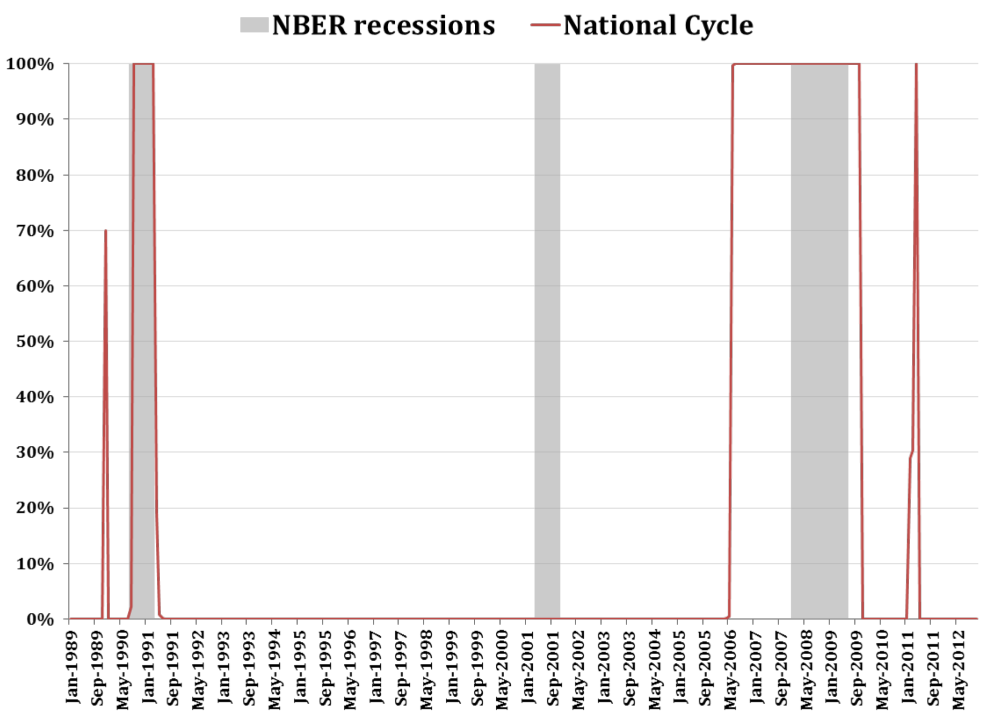
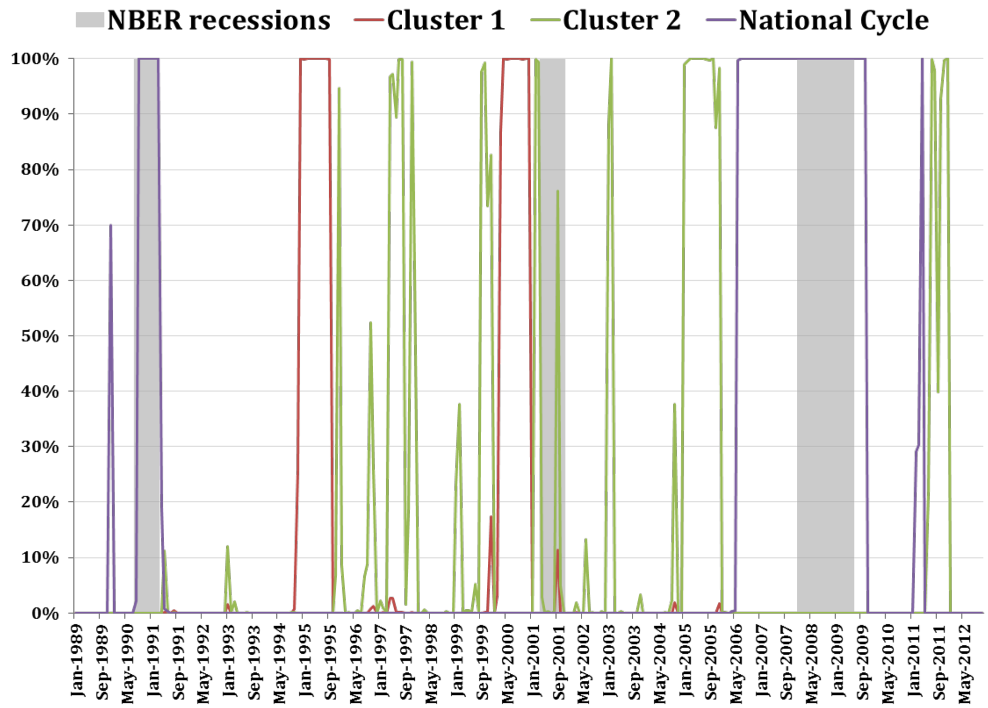


Figure 4: Posterior Probabilities. National Cycle and Idiosyncratic Clusters

(a) Clusters 1 and 2



(b) Clusters 3 and 4

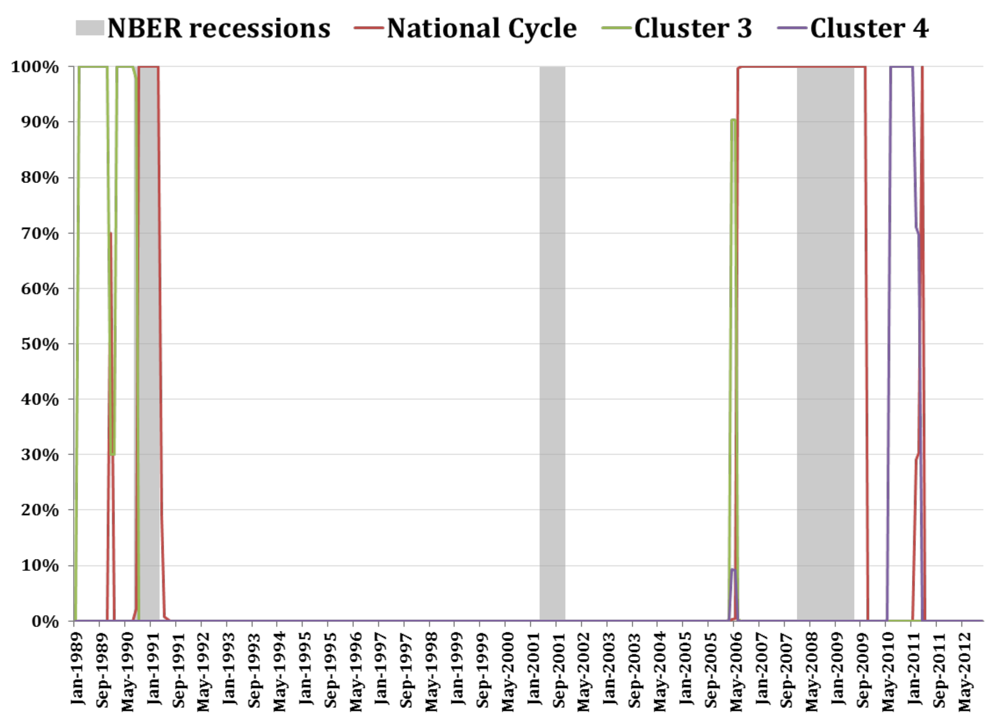


Figure 5: Cluster probabilities