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Clustered Housing Cycles*

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Abstract

Past studies have argued that housing is an important driver of business cycles. Housing markets, however, are highly localized, while business cycles are often measured at the national level. We model a national housing cycle using a panel of cities while also allowing for idiosyncratic departures from the national cycle. These departures occur for clusters of cities that experience simultaneous idiosyncratic housing recessions. We estimate the clustered Markov-switching model proposed in Hamilton and Owyang (2012) using city-level building permits data, a series commonly used at the national level as a business cycle indicator. 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 the 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 geographic constraints in 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

Housing is an important component of the business cycle. 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]. The view of the relationship between housing and the macroeconomy has also led to a flourishing stream of the literature that embeds housing markets into general equilibrium models [see Iacoviello (2005); Iacoviello and Neri (2010)].

This apparently causal relationship between housing and the business cycle, however, is less clear when examining sub-national data. Business cycles are typically measured at a national level while housing markets are highly localized.[2] This geographic disconnect can present problems for macroeconomic analysis. For example, Leamer (2007) argues that housing *is* the business cycle at a national level; Davis and Heathcote (2005) also analyze the relationship between housing and the business cycle. Ghent and Owyang (2010), however, find that, while housing cycles exist at disaggregate levels, the relationship between business cycles and housing appears to break down at sub-national levels.[3]

What accounts for the apparent discrepancy between housing and business cycles at the national and sub-national levels? One hypothesis is that there is, indeed, a national cycle across all housing markets, but this more pervasive cycle is lost amid a large number of deviations once the data is disaggregated: Housing cycles may depend on local factors in addition to national factors. These deviations can take the form of small timing differences – i.e., cities are just out of sync enough that the average cycle does not match the national cycle – or major, city-level, idiosyncratic departures

[1] Housing affects GDP both from the demand and supply sides. On the one hand, housing wealth effects lead to a correlation between housing and consumption expenditures. On the other hand, changes in housing wealth are typically accompanied by changes in housing investment in the same direction, contributing to output and employment. In fact, what we actually observe is that residential fixed investment leads non-housing investment and is more than twice as volatile [see Davis and Heathcote (2005)].

[2] A few papers have modeled sub-national business cycles. For example, Carlino and Sill (2001) examine common cycles across states; Owyang, Piger, and Wall (2005) document variation and similarities in state-level business cycles using Markov switching models. Owyang, Piger, Wall, and Wheeler (2008) perform a similar analysis for cities.

[3] A number of papers show that the relevant unit of analysis for housing is sub-national. Glaeser et al. (2011) suggest that the variation in city-level house prices comes primarily from city-specific, rather than national, factors. Del Negro and Otrok (2007) construct national, state, and regional factors for housing prices and show that the sub-national factors explain more of the variance in housing prices. Ng and Moench (2010) study housing cycles taking into account also the regional variation. They find that shocks at the national level have larger effects than regional shocks. Stock and Watson (2010) show that building permits co-move across states but that housing markets can be uncorrelated across regions.

from the national cycle. If the former is true, we should be able to detect a pervasive national cycle once we account for the deviations. If the latter is true, we may still detect individual city-level cycles but we will not find a pervasive national-level cycle.

We are interested in whether and how city-level housing cycles are related to each other. Common movements in housing volumes across cities may explain why a national-level cycle exists. But correlated idiosyncratic cycles for small numbers of cities, which could contaminate the estimation of the national cycle, may also be important.

What creates the correlation of cycles across cities? One might surmise that the business cycle leads to income effects which then feed into housing cycles. Also, as there is a single monetary policy for all regions, financing conditions will be similar. Furthermore, part of the house price movements will have a common source stemming from changes in interest rates at a national level, producing correlated wealth effects across regions.

In this paper, we consider a set of data thought to be representative of business cycles, at least at a national level. We use current (December 2009) Metropolitan Statistical Area (MSA) definitions to construct time series of MSA-level building permits aggregated from county-level data.[4] We then estimate the clustered Markov-switching model of Hamilton and Owyang (2012, henceforth HO). The HO model estimates a Markov-switching model using panel data. In HO, there exist national expansion and contraction phases. During each of these phases, all of the cities will be in expansion or contraction, respectively. The cities are also grouped together in clusters. Cities in the same cluster experience simultaneous idiosyncratic contractions, which could lead, lag, or occur completely separately from national contractions.

An advantage of the HO model is that it determines the key factors in grouping the cities – i.e., it creates endogenous "regions." For example, 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 six covariates: housing density, population growth, the share of manufacturing employment, average winter temperature, the average unemployment rate, and Saiz's (2010) index of undevelopable land.

We find that there exists a national housing cycle that appears to be similar to the national

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

business cycle. We also find that 4 (overlapping) clusters of cities 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, in part, some of the factors that affect cluster composition. For the most part, these factors appear to be proxies of city-level housing demand characteristics rather than housing supply characteristics or factors that influence business cycle similarity.

The balance 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

The model requires two sets of data: the panel of city-level housing indicators and the cross-section of covariate data used for clustering. In this section, we outline these data. As our housing indicators, we use city-level permits. Much of the recent work has focused on house price dynamics. Leamer (2007), however, argues that housing volumes may be a better indicator of business cycle dynamic than house prices.

2.1 City-level Building Permits

City-level building permit data are available for various time periods for the majority of cities. However, MSA definitions have changed a number of times over the years, causing a problem for cycle analysis because the models typically require long time series to detect switching between phases. If we were to use existing MSA-level data for our analysis, we would be limited in the number of cities with available data, and for most cities the level data are only available since the mid-1990s. Therefore, we opt to construct an MSA-level permits series by aggregating up from county-level data. To avoid issues with MSA definitions, we sum county-level data using the counties that are in the December 2009 MSA definitions.

County-level building permits data are released monthly but are measured as permits year-to-date. Ordinarily, this would not present a problem as simple differencing of the data would provide the monthly flow. However, the year-to-date data are constantly revised, making it difficult to determine whether a change from month to month is caused by a change in the level or permits for the past month or if it is caused by a revision that affects all past months. In addition, the data at a monthly frequency can be noisy, which might affect the filter used to detect switches in cycle phase. To mitigate these two problems, we use the two-month moving average of the year-over-year growth rate of building permits.[5]

Our sample consists of data from 1989:03 to 2012:11. While our complete dataset consists of 277 MSAs, we utilize only the 143 cities with population greater than 250,000 residents (based on 1990 populations computed with the current MSA definition) for which all covariates are available. We do this for two reasons. First, the data for the small cities are inherently noisier. Limiting ourselves to the larger cities mitigates this problem. Second, because the model searches for correlation across cities, clustering in larger panels will be more cumbersome and less likely to be precisely estimated.

[Figure permits growth here]

Figure 1 depicts the building permits growth series for a few of the cities in our sample. The national data are included as a baseline for comparison. The shaded areas are NBER contraction dates. The national data have a clear cyclical pattern that is roughly coincident with the timing of the NBER contractions. The U.S. experiences some fluctuations apart from the business cycle dates but the largest downturns begin just before an NBER-defined peak.[6] City-level experiences vary widely. Chicago, for example, behaves very similarly to the nation. Los Angeles has the same broad features as the nation but appears to have more "mini" cycles. The Reno-Sparks, NV, permit series experiences even more of these mini cycles, almost to the point that the series appears to be seasonal. Table 8 in the Appendix contains the full list of cities in our sample and summary statistics of the growth series.

[5]Year-over-year growth rates could alter the estimated timing of switching in the housing cycle phases by a month or so. However, because our emphasis is on the correlation of the cycles rather than exact dating of the cycles, the effect should be minimized.

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

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

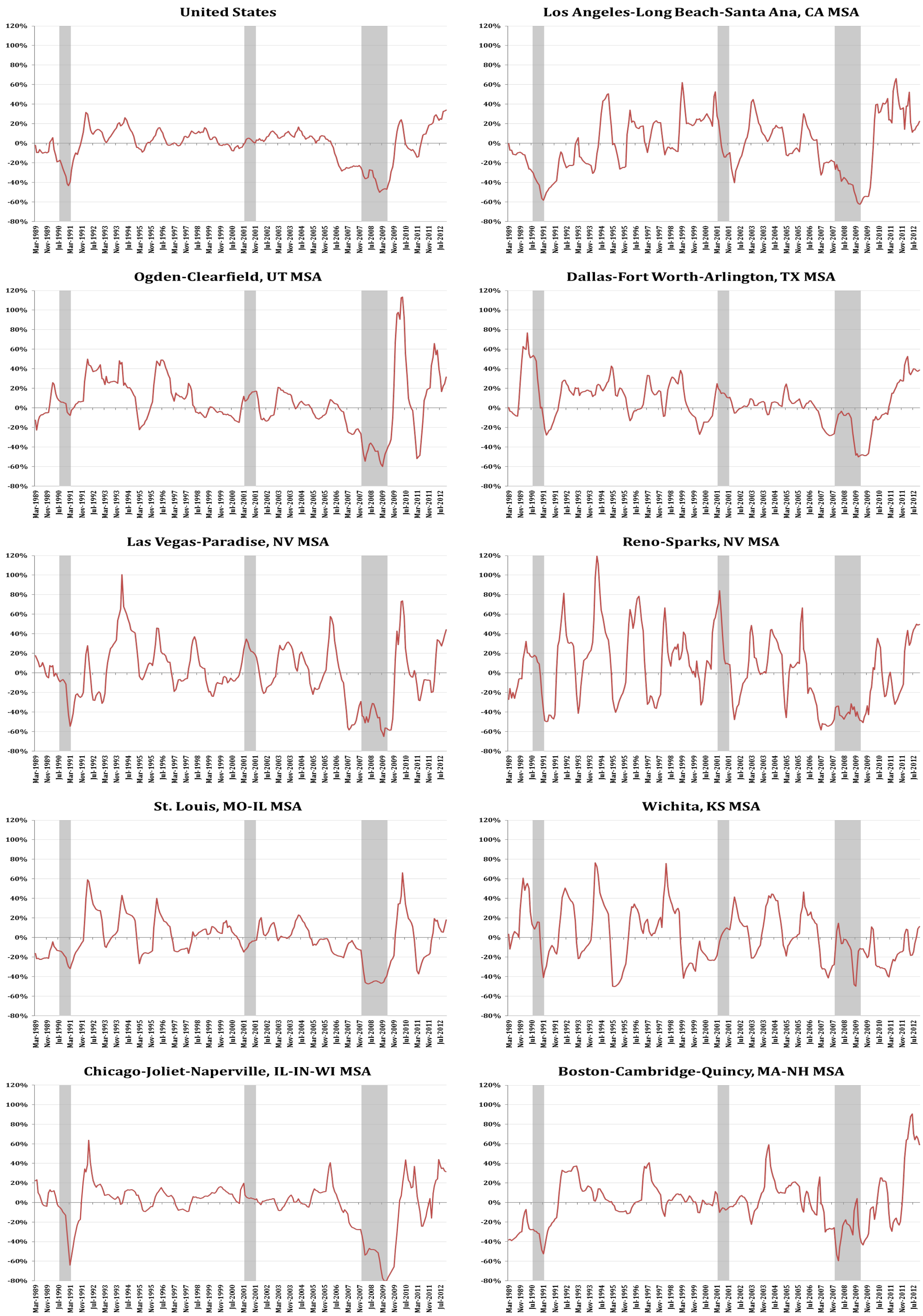


Table 1: Covariates Summary Statistics

Covariate	Mean	SD	Median	Min	Max
Housing units per sq. km. 1990	59.8	40.7	58.2	4.1	380.7
Avg. population growth (%) 1970–1990	1.4	1.2	1.3	-0.6	6.0
Manufacturing employment share (%) 1990	21.3	20.1	8.3	3.2	58.5
Average winter temperature (° Celsius)	4.4	3.1	6.9	-9.6	19.6
Average unemployment rate (%) 1988–2012	6.0	5.6	1.8	3.3	14.2
Saiz's (2010) index of undevelopable land (%)	27.8	22.3	21.5	0.9	86.0

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.

2.2 Covariate Data

The estimation of the HO model can include a set of covariates used to specify a logistic meta prior that helps determine/explain how the city series are clustered. Some of the data do not change over time. Data that do vary over time are fixed across the cross-section by either taking an average or snapshot at some point of the sample. For example, the industrial composition of some cities will vary over the time sample but we take as fixed the manufacturing share computed using data from 1990.

[Table covariates summary statistics here]

In addition to the manufacturing share, we obtain the average population growth over the period 1970 to 1990, the average winter temperature, the average unemployment rate, the housing density, and Saiz's (2010) index of undevelopable land. Table 1 presents summary statistics of the cross-section of covariates.[7] First, the manufacturing share has been shown to be a determinant of business cycle similarity. Thus, we are able to consider whether a variable affecting business cycle similarity also determines housing cycle similarity. We also consider whether cities with

[7]The average population growth is taken from the Census and represents the percent increase in the population of the counties in the 2009 definition of the MSA between 1970 and 1990. The share of manufacturing employment is computed from county-level data. 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. Saiz's (2010) index represents the proportion of area in each city that cannot be developed because of geographic constraints.

similar demands for new housing would have similar cycles. Population growth is a proxy for the average change in housing demand, as higher average population growth suggests a higher average demand for new housing. The unemployment rate represents long-run differences in local economic conditions that may also affect the demand for housing. Average winter temperature may be another proxy for housing demand, especially by a higher income demographic. Housing density is a proxy for the supply of housing and Saiz's index of undevelopable land reflects geographic constraints on the elasticity in the supply of housing.

3 The Empirical Model

The model we adopt 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 can be accomplished 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, we obtain a model with national contractions and expansions and periods during which some 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).[8]

[8]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, Segers, and van Dijk (2009) and Leiva-Leon (2012).

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 $S_{nt} = 1$ 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 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 $E(\varepsilon_t \varepsilon_t^{'}) = \mathbf{\Sigma}$, where we assume that the covariance matrix is diagonal with representative element σ_n^2. The diagonality restriction is made for parsimony and means that correlation across cities is driven primarily through simultaneity in their cycles.

We can summarize the individual S_{nt} with a scalar aggregate regime Z_t that signifies the time-t aggregate regime. Let $\mathbf{H}$ denote an $(N \times K)$ matrix whose elements are all zeros and ones and 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 $K = 3$, suggesting 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 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.[9]

[9]We do not refer to idiosyncratic expansions as these are simply idiosyncratic recessions for the complimentary

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 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 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 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.[10]

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

set of states.

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

by a collection of univariate Markov switching models.

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,

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}	$\Gamma\left(\frac{\nu}{2}, \frac{\delta}{2}\right)$	$\nu = 2$; $\delta = 2$	$\forall n$
$\mathbf{P}$	$\mathbf{D}(\alpha)$	$\alpha_i = 0$	$\forall i$
β_k	$N(\mathbf{b}, \mathbf{B})$	$\mathbf{b} = \mathbf{0}_p$; $\mathbf{B} = \frac{1}{2}\mathbf{I}_p$	$\forall k$

$\mathbf{Z_T}$; 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

[Table priors here]

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 parameters θ_n is 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, 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 were considering states, the number of clusters was assumed to be small and only a small number of marginal likelihoods were required to determine K.

We have a large number of cities, requiring a larger number of marginal likelihood computations. Because the methods used to compute the marginal likelihoods are time consuming, we opted to compute 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 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 process, and the cluster compositions.

5.1 Growth Rates

[Tables parameters here]

The model posits that city-level permits take on two average values over the housing cycle, essentially a mixture of the two distributions. 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

Table 3: Top and Bottom μ_0

Cities with lowest μ_0		
CBSA	MSA	μ_0
10420	Akron, OH MSA	0.0183
15380	Buffalo-Niagara Falls, NY MSA	0.0324
17460	Cleveland-Elyria-Mentor, OH MSA	0.0342
40380	Rochester, NY MSA	0.0356
33340	Milwaukee-Waukesha-West Allis, WI MSA	0.0368
49660	Youngstown-Warren-Boardman, OH-PA MSA	0.0373
17140	Cincinnati-Middletown, OH-KY-IN MSA	0.0450
47300	Visalia-Porterville, CA MSA	0.0465
41420	Salem, OR MSA	0.0486
28020	Kalamazoo-Portage, MI MSA	0.0553
Cities with highest μ_0		
CBSA	MSA	μ_0
17820	Colorado Springs, CO MSA	0.2662
32580	McAllen-Edinburg-Mission, TX MSA	0.2678
41500	Salinas, CA MSA	0.2708
19780	Des Moines-West Des Moines, IA MSA	0.2712
33860	Montgomery, AL MSA	0.2859
45940	Trenton-Ewing, NJ MSA	0.3127
13140	Beaumont-Port Arthur, TX MSA	0.3425
41700	San Antonio-New Braunfels, TX MSA	0.3679
12420	Austin-Round Rock-San Marcos, TX MSA	0.3845
28660	Killeen-Temple-Fort Hood, TX MSA	0.4200

Table 4: Top and Bottom $\mu_0 + \mu_1$

Cities with lowest $\mu_0 + \mu_1$		
CBSA	MSA	$\mu_0 + \mu_1$
15980	Cape Coral-Fort Myers, FL MSA	-0.5382
38940	Port St. Lucie, FL MSA	-0.5082
33700	Modesto, CA MSA	-0.4460
33100	Miami-Fort Lauderdale-Pompano Beach, FL MSA	-0.4424
37100	Oxnard-Thousand Oaks-Ventura, CA MSA	-0.4393
19820	Detroit-Warren-Livonia, MI MSA	-0.4220
22420	Flint, MI MSA	-0.4191
40140	Riverside-San Bernardino-Ontario, CA MSA	-0.4177
44700	Stockton, CA MSA	-0.4101
40420	Rockford, IL MSA	-0.3896
Cities with highest $\mu_0 + \mu_1$		
CBSA	MSA	$\mu_0 + \mu_1$
32580	McAllen-Edinburg-Mission, TX MSA	-0.0877
15180	Brownsville-Harlingen, TX MSA	-0.0706
46140	Tulsa, OK MSA	-0.0575
33660	Mobile, AL MSA	-0.0568
16620	Charleston, WV MSA	-0.0514
35380	New Orleans-Metairie-Kenner, LA MSA	-0.0489
12420	Austin-Round Rock-San Marcos, TX MSA	-0.0466
30780	Little Rock-North Little Rock-Conway, AR MSA	-0.0266
21500	Erie, PA MSA	0.0360
13140	Beaumont-Port Arthur, TX MSA	0.1275

Table 5: Top and Bottom σ^2

Cities with lowest σ^2		
CBSA	MSA	σ^2
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA	0.0181
39300	Providence-New Bedford-Fall River, RI-MA MSA	0.0195
47260	Virginia Beach-Norfolk-Newport News, VA-NC MSA	0.0198
40380	Rochester, NY MSA	0.0215
16980	Chicago-Joliet-Naperville, IL-IN-WI MSA	0.0219
38300	Pittsburgh, PA MSA	0.0222
26900	Indianapolis-Carmel, IN MSA	0.0223
41180	St. Louis, MO-IL MSA	0.0227
17460	Cleveland-Elyria-Mentor, OH MSA	0.0228
17140	Cincinnati-Middletown, OH-KY-IN MSA	0.0232
Cities with highest σ^2		
CBSA	MSA	σ^2
44060	Spokane, WA MSA	0.1364
22420	Flint, MI MSA	0.1387
46700	Vallejo-Fairfield, CA MSA	0.1619
45940	Trenton-Ewing, NJ MSA	0.1905
42060	Santa Barbara-Santa Maria-Goleta, CA MSA	0.2294
21500	Erie, PA MSA	0.2404
41940	San Jose-Sunnyvale-Santa Clara, CA MSA	0.2698
28660	Killeen-Temple-Fort Hood, TX MSA	0.2844
13140	Beaumont-Port Arthur, TX MSA	0.3065
41500	Salinas, CA MSA	0.3232

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.[11]

[Figures parameters maps here]

As would be expected, there are large differences in the means across cities but, perhaps surprisingly, there are no obvious 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 38.2 percent.

Perhaps not surprisingly, cities with high growth rates also typically have higher conditional variance: the correlation between μ_0 and σ^2 is 61.2 percent. Because the model is somewhat restrictive for the cycle process to achieve parsimony, idiosyncratic city-level fluctuations will manifest as shocks. Cities with large average growth rates that experience these idiosyncratic shocks will then tend to have larger variances of these shocks.

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.

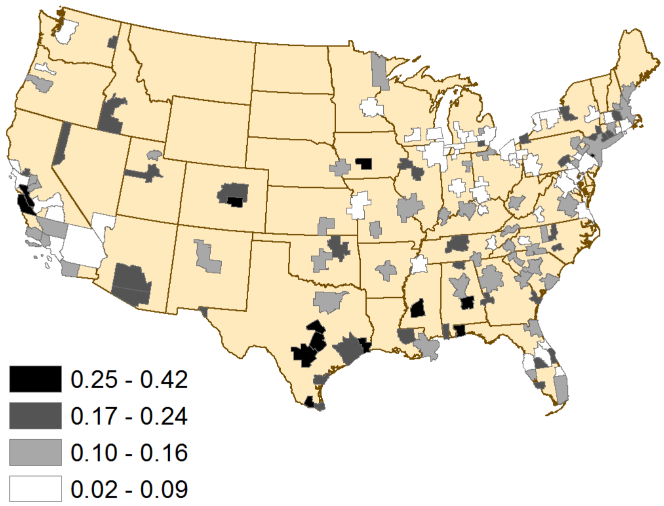
[Figure national cycle here]

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 dichotomous outcomes: national housing expansion or contraction. A few things to note. First, the nation experiences two major housing

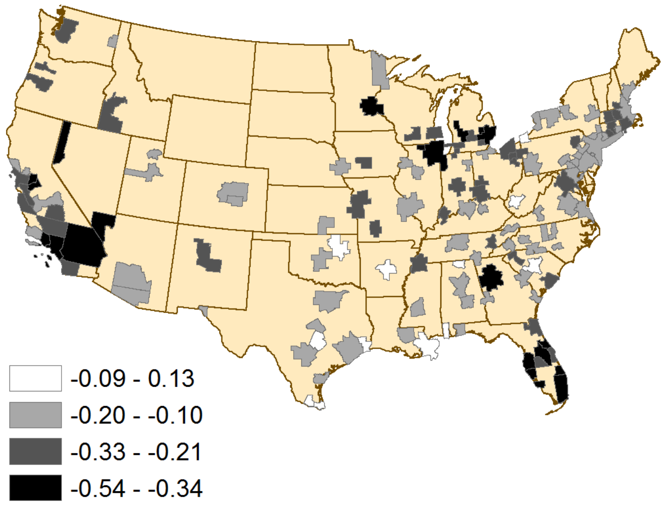
[11] Table 8 in the Appendix shows the mean growth rates and the city-level variances for all of the 143 cities in our sample and includes the mean and sample standard deviation of each city's raw building permits growth series.

Figure 2: Model estimates

(a) μ_0



(b) $\mu_0 + \mu_1$



(c) σ^2

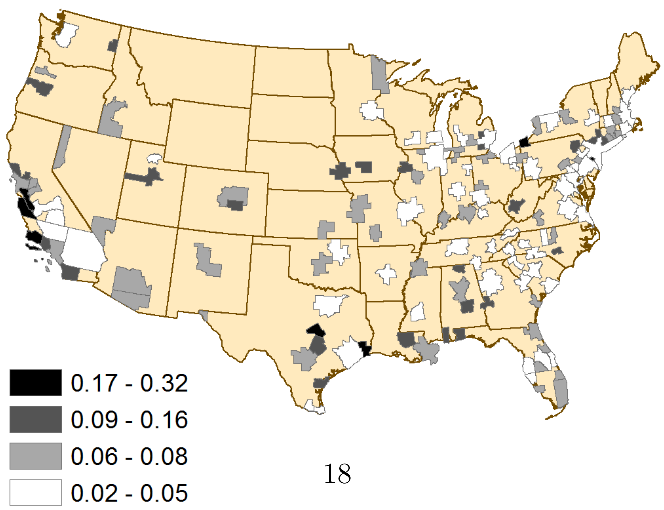
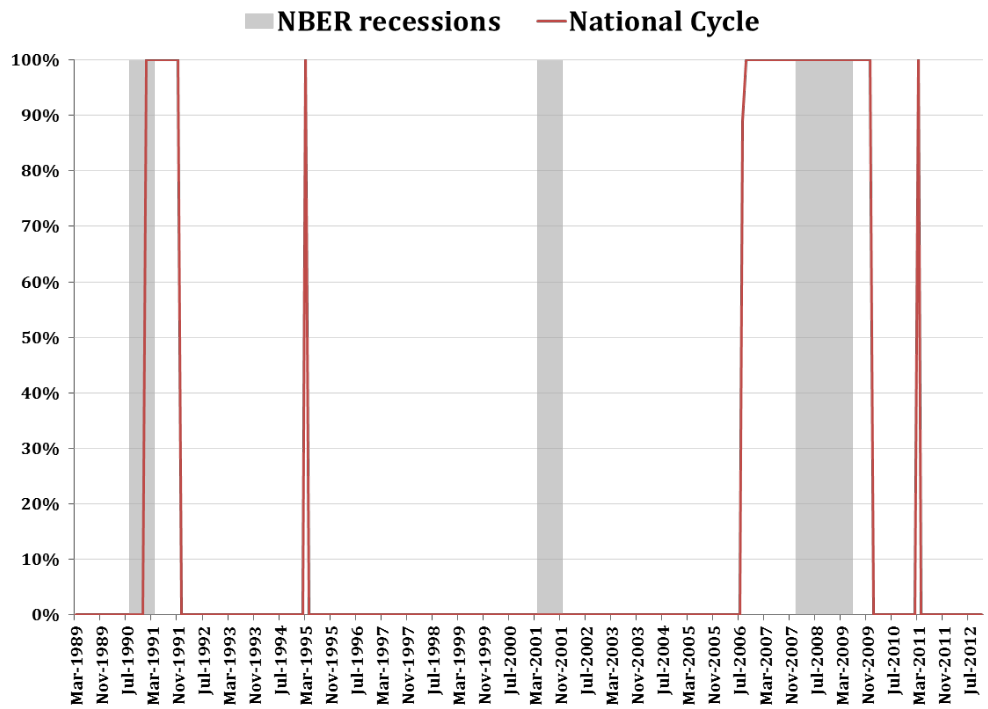


Figure 3: Posterior Probabilities of a National Level Housing Recession



downturns, the first around the 1991 NBER recession and the second around the 2007-2009 NBER recession, although the housing contraction lasts a little longer in both cases. The second episode was an economic downturn that was associated with a decline in the housing market and the housing market had a sustained downturn that lasted longer than the downturn in output. The timing, therefore, is not surprising.

Second, when the aggregate regime switches to the national housing contraction, it does so, for the most part, with little uncertainty – that is, there are very few periods for which the regime probability is between zero and one.

Third, there appear to be a few instances of national housing contraction that are not associated with national recessions, but they are short-lived.

Finally, a national housing contraction does not occur during the 2001 NBER recession in our sample. This 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

Table 6: Transition Probabilities

	To Exp	**To Rec**	**To C1**	**To C2**	**To C3**	**To C4**
From Exp	0.946	0.015	0.008	0	0.031	0
From Rec	0	0.926	0	0.037	0	0.037
From C1	0.091	0	0.909	**0**	**0**	**0**
From C2	0.143	0	**0**	0.857	**0**	**0**
From C3	0.053	0.036	**0**	**0**	0.911	**0**
From C4	0.105	0	**0**	**0**	**0**	0.895

by cluster contractions instead of national contractions.[12]

5.3 City-level Housing Cycles

Before we can compare the city-level cycles, we must first determine the number of idiosyncratic clusters. As we indicated above, we can compute a modified Bayesian information criterion (BIC) for a number of different cluster combinations. 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.

[Table transition probabilities here]

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 cycle" 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 $Z_t = k > 3$. 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

[12] Indeed, this period does become a national housing contraction if we reduce the number of idiosyncratic clusters. However, as we will see below, a model with a larger number of idiosyncratic clusters is preferred. This suggests that the clusters contain a large number of cities but a number well short of the full cross section.

estimated transition probabilities for the aggregate regime variable, Z_t. The 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. This means that the model finds no transitions between, say, from $Z_t = 2$ to $Z_{t+1} = 1$. How can this occur? The data indicate that transitions from national contractions to national expansions can only occur through one of the cluster contractions. That is, there is always a group of cities which stay in contraction longer than the nation.

Figure 4 plots the posterior probabilities of the idiosyncratic clusters. We also plot the probability of the national contraction in each panel. The idiosyncratic clusters take a number of forms: (1) cities that experience idiosyncratic contractions (cluster 1) and (2) cities that stay in contraction after the nation exits (cluster 2 and cluster 4, but only for those national housing downturns that do not coincide with NBER recessions). Cities in cluster 3 enter contractions when other cities are in expansions but are not indicators of future national recessions. These cities can have either idiosyncratic contractions or be precursors to national contractions.

[Figures clusters here]

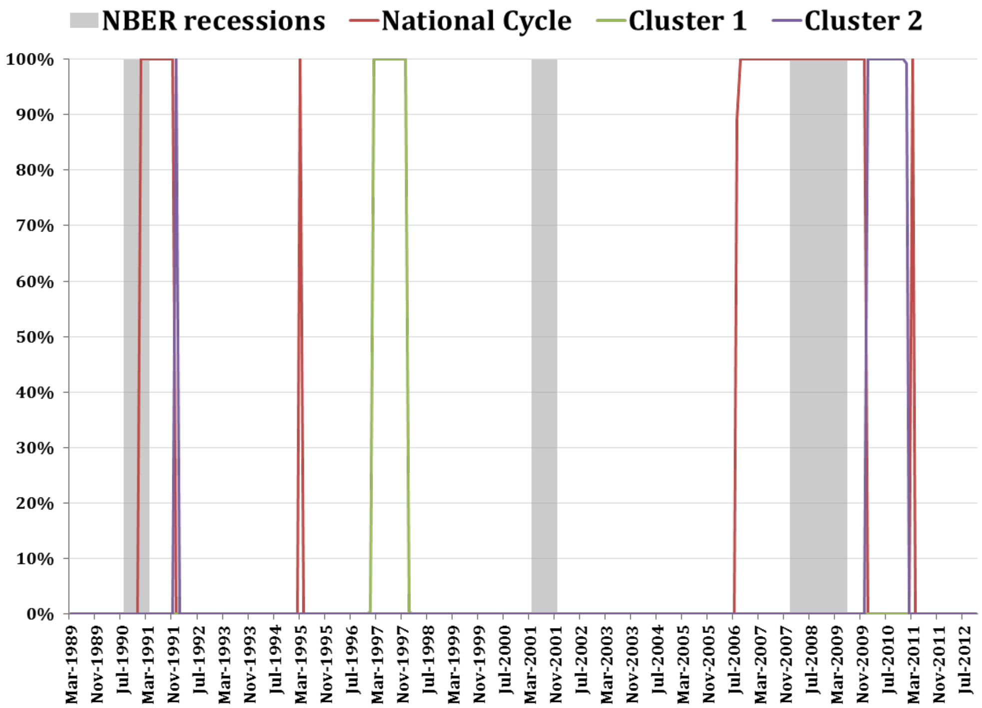
[Figures cluster membership probabilities maps here]

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.

Cluster 1 contains cities all across the country without an obvious geographical or industrial pattern. For example, cluster 1 contains cities in the Southeast, Midwest, and central California. The predominant feature of these cities' housing experiences is that they all contracted in 1997 while the rest of the nation expanded. Cluster 2 contains cities mostly in the south central and southeastern U.S. but also includes Washington, D.C. and the New York MSA. These cities stayed in contraction after the end of the financial crisis period, while other cities began to recover. Cluster 3 experienced idiosyncratic contractions during the late 1990s through the financial crisis and contained much of the Northeast, the South, and Phoenix, AZ. Finally, cluster 4 contains cities in California, New England, Arizona, Texas, the South, and the Midwest. Geography and size (population) therefore do not appear to be key determinants of cluster composition.

Figure 4: Posterior Probabilities. National Cycle and Idiosyncratic Clusters

(a) Clusters 1 and 2



(b) Clusters 3 and 4

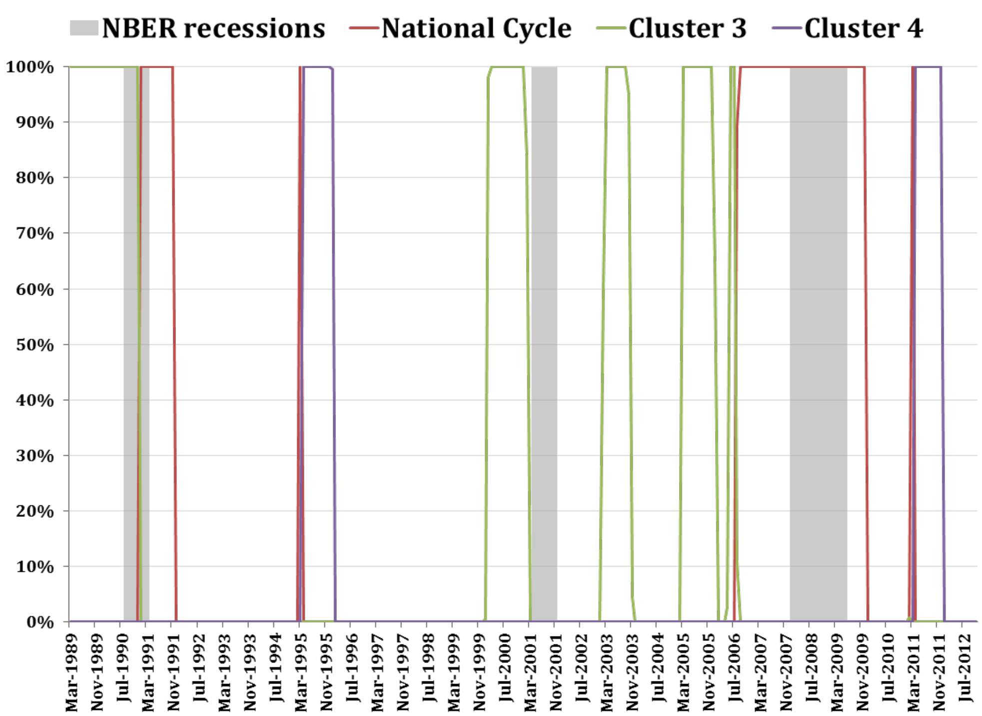


Figure 5: Cluster probabilities

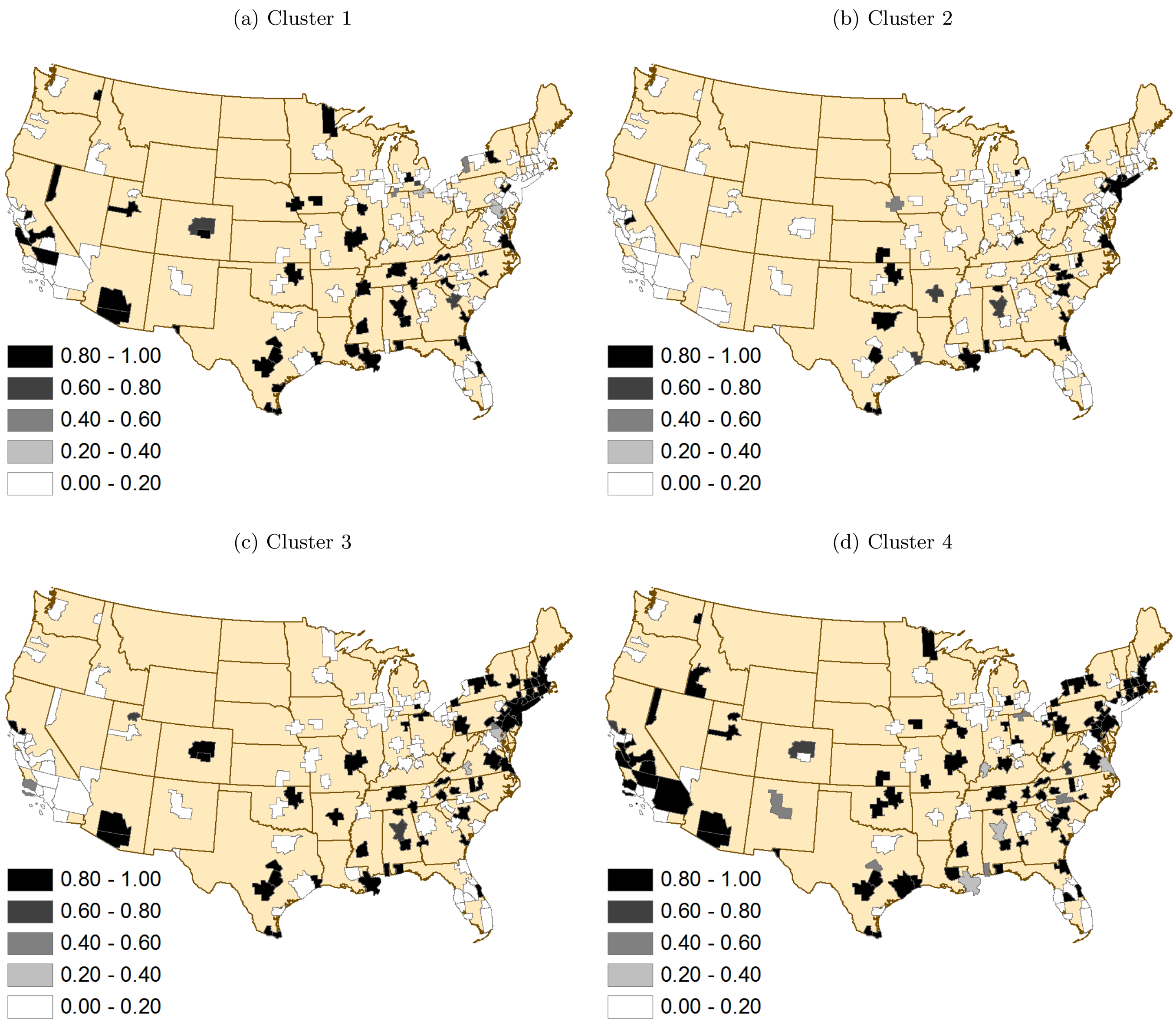


Table 7: Effect of the Covariates

Covariate	β_1	β_2	β_3	β_4
Constant	**-1.038**	**-1.896**	**-0.329**	**0.643**
Housing units per sq. km. 1990	**-0.243**	0.010	-0.012	**-0.201**
Average population growth 1970-1990	-0.108	-0.037	-0.109	-0.137
Manufacturing employment share 1990	**-0.112**	0.036	0.099	0.083
Average winter temperature (° Celsius)	**0.121**	**0.104**	0.120	0.076
Average unemployment rate (%) 1989-2012	0.043	0.010	**-0.145**	0.065
Saiz's index of undevelopable land (%)	-0.073	-0.061	0.017	0.016

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.

5.4 What Factors Affect the Comovements

[Table effects covariates here]

We observed from the previous section that geography, size (population), and/or industrial composition do not appear to be the only determinants of cluster composition. To determine other factors that create similarities in city-level housing cycles, we included a small set of city-level covariates in the hierarchical logistic prior for the clustering algorithm. 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.

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.[13] We find that housing demand covariates play an important role for determining two of the clusters (2 and 3). In general, changes in the average population and the amount of undevelopable land do not appear to play an important role in synchronizing cities' housing cycles.[14]

[13]The bold coefficient can be thought of as similar to having a p-value of less than 0.05.

[14]This result does not suggest that these factors are not important for housing markets in general. They may play

Cluster 1 is composed of cities that experience an idiosyncratic contraction in the late 1990s. These cities tend to have lower housing density, lower manufacturing share, and higher average winter temperature. For cluster 2, the common characteristic appears to be higher than average winter temperatures. Cluster 3 primarily consists of cities with lower unemployment rates.

Only cluster 4 appears to be principally determined by a supply factor. Cities in this cluster have lower, on average, housing density, suggesting that it is more likely that they have flexibility in their long run housing supply.

The former result suggests that the determinants of housing cycle similarity differ substantially from the determinants of business cycle similarity. This result reinforces the notion proposed by Ghent and Owyang (2010) that, at a subnational level, housing cycles and business cycles are not as connected as they appear to be at a national level. In general, these results appear to suggest that housing demand, not supply, is the main determinant of similarities in the cyclical fluctuations in housing. Perhaps this 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 sub-national 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 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

a role in determining similarities in the trends in housing markets and may be more important for prices than for permits.

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.

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7 Lists of Cities

Table 8: List of Cities and Growth Statistics and Results

Rank	CBSA	MSA	Mean	SD	μ_0	μ_1	σ^2
60	10420	Akron, OH MSA	-4.1	25.1	0.0183	-0.3211	0.0409
48	10580	Albany-Schenectady-Troy, NY MSA	-1.4	24.2	0.0655	-0.2125	0.0445
65	10740	Albuquerque, NM MSA	3.1	27.2	0.1145	-0.3583	0.0522
53	10900	Allentown-Bethlehem-Easton, PA-NJ MSA	-2.2	24.2	0.1339	-0.2975	0.0319
129	11460	Ann Arbor, MI MSA	2.0	44.1	0.1732	-0.4183	0.1026
119	11700	Asheville, NC MSA	0.5	22.8	0.1204	-0.2544	0.0365
12	12060	Atlanta-Sandy Springs-Marietta, GA MSA	1.0	27.4	0.0994	-0.4757	0.0384
82	12260	Augusta-Richmond County, GA-SC MSA	3.1	22.9	0.0991	-0.2404	0.0411
45	12420	Austin-Round Rock-San Marcos, TX MSA	15.6	41.2	0.3845	-0.4311	0.1148
70	12540	Bakersfield-Delano, CA MSA	1.2	30.0	0.1378	-0.4418	0.0435
19	12580	Baltimore-Towson, MD MSA	-1.2	23.0	0.0706	-0.2632	0.0379
63	12940	Baton Rouge, LA MSA	8.4	36.5	0.1839	-0.3648	0.0916
102	13140	Beaumont-Port Arthur, TX MSA	23.8	57.5	0.3425	-0.2150	0.3065
42	13820	Birmingham-Hoover, AL MSA	3.0	26.6	0.1537	-0.3129	0.0501
117	14260	Boise City-Nampa, ID MSA	9.3	35.6	0.2351	-0.5541	0.0696
6	14460	Boston-Cambridge-Quincy, MA-NH MSA	0.4	24.9	0.1324	-0.2907	0.0364
47	14860	Bridgeport-Stamford-Norwalk, CT MSA	6.3	38.0	0.1772	-0.2828	0.1091
139	15180	Brownsville-Harlingen, TX MSA	7.8	28.7	0.2290	-0.2996	0.0459
34	15380	Buffalo-Niagara Falls, NY MSA	-1.2	28.5	0.0324	-0.1757	0.0681
92	15940	Canton-Massillon, OH MSA	-0.6	25.8	0.0693	-0.3146	0.0410
114	15980	Cape Coral-Fort Myers, FL MSA	4.4	36.1	0.1794	-0.7176	0.0522
120	16620	Charleston, WV MSA	4.8	34.9	0.1289	-0.1803	0.1127
75	16700	Charleston-North Charleston-Summerville, SC MSA	4.5	22.9	0.1208	-0.3937	0.0287
39	16740	Charlotte-Gastonia-Rock Hill, NC-SC MSA	4.0	29.9	0.1168	-0.3222	0.0482
83	16860	Chattanooga, TN-GA MSA	-1.2	20.4	0.1151	-0.2577	0.0255
3	16980	Chicago-Joliet-Naperville, IL-IN-WI MSA	-1.3	23.8	0.0731	-0.4220	0.0219
23	17140	Cincinnati-Middletown, OH-KY-IN MSA	-1.8	20.4	0.0450	-0.3379	0.0232
21	17460	Cleveland-Elyria-Mentor, OH MSA	-2.5	19.7	0.0342	-0.3165	0.0228
89	17820	Colorado Springs, CO MSA	9.7	40.6	0.2662	-0.4206	0.1021

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Rank	CBSA	MSA	Mean	SD	μ_0	μ_1	σ^2
69	17900	Columbia, SC MSA	2.4	19.4	0.1361	-0.2240	0.0247
138	17980	Columbus, GA-AL MSA	5.9	34.5	0.2063	-0.3216	0.0944
100	18580	Corpus Christi, TX MSA	10.1	32.9	0.1805	-0.3502	0.0882
9	19100	Dallas-Fort Worth-Arlington, TX MSA	6.1	21.9	0.1334	-0.3076	0.0300
99	19340	Davenport-Moline-Rock Island, IA-IL MSA	8.8	36.5	0.1727	-0.3505	0.1010
46	19380	Dayton, OH MSA	0.5	30.0	0.0834	-0.3416	0.0520
96	19660	Deltona-Daytona Beach-Ormond Beach, FL MSA	-2.6	28.6	0.0573	-0.4375	0.0532
24	19740	Denver-Aurora-Broomfield, CO MSA	6.6	30.8	0.2120	-0.3155	0.0694
88	19780	Des Moines-West Des Moines, IA MSA	11.0	43.3	0.2712	-0.5574	0.1172
5	19820	Detroit-Warren-Livonia, MI MSA	0.1	34.5	0.0760	-0.4981	0.0424
135	20260	Duluth, MN-WI MSA	3.9	27.8	0.1140	-0.2599	0.0617
108	20500	Durham-Chapel Hill, NC MSA	8.7	37.3	0.1922	-0.3062	0.0838
66	21340	El Paso, TX MSA	9.1	32.9	0.2067	-0.3936	0.0771
133	21500	Erie, PA MSA	16.5	61.0	0.2114	-0.1754	0.2404
130	21660	Eugene-Springfield, OR MSA	7.2	35.1	0.1572	-0.4475	0.0937
116	21780	Evansville, IN-KY MSA	5.1	35.1	0.1338	-0.4276	0.0795
123	22180	Fayetteville, NC MSA	10.4	39.4	0.2032	-0.3483	0.1260
86	22420	Flint, MI MSA	4.2	54.0	0.1487	-0.5678	0.1387
105	23060	Fort Wayne, IN MSA	-0.9	21.4	0.1007	-0.2524	0.0249
57	23420	Fresno, CA MSA	-0.6	25.8	0.0780	-0.2840	0.0477
62	24340	Grand Rapids-Wyoming, MI MSA	-1.8	23.9	0.0599	-0.4132	0.0314
71	24660	Greensboro-High Point, NC MSA	0.8	22.7	0.1246	-0.2601	0.0334
79	24860	Greenville-Mauldin-Easley, SC MSA	4.5	29.5	0.1239	-0.3857	0.0459
78	25420	Harrisburg-Carlisle, PA MSA	1.5	29.6	0.1729	-0.3515	0.0557
35	25540	Hartford-West Hartford-East Hartford, CT MSA	-2.1	30.0	0.1416	-0.3644	0.0545
127	25860	Hickory-Lenoir-Morganton, NC MSA	-2.3	22.3	0.0727	-0.1919	0.0413
10	26420	Houston-Sugar Land-Baytown, TX MSA	9.9	25.5	0.1824	-0.3220	0.0459
126	26620	Huntsville, AL MSA	6.9	36.0	0.2330	-0.3262	0.1046
31	26900	Indianapolis-Carmel, IN MSA	0.5	19.9	0.0683	-0.3256	0.0223
80	27140	Jackson, MS MSA	5.3	38.9	0.2538	-0.4567	0.0432
44	27260	Jacksonville, FL MSA	1.8	29.7	0.1408	-0.3742	0.0502
125	28020	Kalamazoo-Portage, MI MSA	0.2	30.9	0.0553	-0.2925	0.0792
25	28140	Kansas City, MO-KS MSA	1.4	27.6	0.0885	-0.3850	0.0525

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Rank	CBSA	MSA	Mean	SD	μ_0	μ_1	σ^2
136	28660	Killeen-Temple-Fort Hood, TX MSA	25.4	101.3	0.4200	-0.5611	0.2844
132	28700	Kingsport-Bristol-Bristol, TN-VA MSA	3.3	27.1	0.1550	-0.2756	0.0346
73	28940	Knoxville, TN MSA	0.8	25.1	0.0916	-0.3254	0.0432
90	29460	Lakeland-Winter Haven, FL MSA	4.0	33.8	0.1655	-0.4896	0.0700
87	29540	Lancaster, PA MSA	0.0	24.1	0.1213	-0.2694	0.0396
84	29620	Lansing-East Lansing, MI MSA	-0.9	33.2	0.0899	-0.3787	0.0622
51	29820	Las Vegas-Paradise, NV MSA	0.2	29.0	0.0885	-0.4586	0.0500
107	30460	Lexington-Fayette, KY MSA	0.9	23.2	0.0767	-0.2797	0.0388
72	30780	Little Rock-North Little Rock-Conway, AR MSA	5.8	23.4	0.1222	-0.1488	0.0487
2	31100	Los Angeles-Long Beach-Santa Ana, CA MSA	-1.1	28.2	0.0657	-0.4043	0.0553
37	31140	Louisville/Jefferson County, KY-IN MSA	3.2	27.7	0.1025	-0.2776	0.0615
85	31540	Madison, WI MSA	0.2	22.3	0.0652	-0.3419	0.0300
113	31700	Manchester-Nashua, NH MSA	0.7	39.5	0.1173	-0.3452	0.0695
94	32580	McAllen-Edinburg-Mission, TX MSA	11.2	40.3	0.2678	-0.3555	0.0426
36	32820	Memphis, TN-MS-AR MSA	0.7	28.9	0.0840	-0.3438	0.0622
8	33100	Miami-Fort Lauderdale-Pompano Beach, FL MSA	1.3	35.8	0.0995	-0.5419	0.0515
29	33340	Milwaukee-Waukesha-West Allis, WI MSA	-2.3	22.4	0.0368	-0.3093	0.0349
16	33460	Minneapolis-St. Paul-Bloomington, MN-WI MSA	0.4	29.4	0.0713	-0.4173	0.0422
95	33660	Mobile, AL MSA	10.5	38.7	0.2097	-0.2665	0.0893
97	33700	Modesto, CA MSA	-3.5	40.5	0.1193	-0.5653	0.0591
121	33860	Montgomery, AL MSA	8.3	50.6	0.2859	-0.4639	0.1265
38	34980	Nashville-Davidson–Murfreesboro–Franklin, TN MSA	3.4	28.4	0.2131	-0.3638	0.0483
49	35300	New Haven-Milford, CT MSA	0.7	46.1	0.1764	-0.4467	0.0693
32	35380	New Orleans-Metairie-Kenner, LA MSA	6.5	36.5	0.1394	-0.1883	0.0834
1	35620	New York-Northern New Jersey-Long Island, NY-NJ-PA MSA	1.5	23.3	0.1190	-0.2264	0.0345
76	35840	North Port-Bradenton-Sarasota, FL MSA	2.6	28.7	0.1166	-0.4798	0.0479
142	35980	Norwich-New London, CT MSA	-4.6	27.6	0.0719	-0.2568	0.0608
106	36260	Ogden-Clearfield, UT MSA	5.6	27.8	0.1595	-0.2844	0.0461
41	36420	Oklahoma City, OK MSA	7.5	28.0	0.1515	-0.3196	0.0504
54	36540	Omaha-Council Bluffs, NE-IA MSA	9.9	44.4	0.1448	-0.3009	0.0978
33	36740	Orlando-Kissimmee-Sanford, FL MSA	0.6	25.8	0.0888	-0.4450	0.0346
56	37100	Oxnard-Thousand Oaks-Ventura, CA MSA	1.1	41.8	0.1165	-0.5558	0.1290
91	37340	Palm Bay-Melbourne-Titusville, FL MSA	-1.8	30.4	0.2040	-0.4506	0.0423

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Rank	CBSA	MSA	Mean	SD	μ_0	μ_1	σ^2
109	37860	Pensacola-Ferry Pass-Brent, FL MSA	5.9	40.8	0.2548	-0.4239	0.0914
103	37900	Peoria, IL MSA	6.4	32.6	0.1638	-0.3582	0.0745
4	37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA	-2.6	18.4	0.0784	-0.2255	0.0181
20	38060	Phoenix-Mesa-Glendale, AZ MSA	3.1	29.1	0.2081	-0.3622	0.0526
18	38300	Pittsburgh, PA MSA	-0.5	18.1	0.0889	-0.2079	0.0222
143	38940	Port St. Lucie, FL MSA	-3.0	33.1	0.1229	-0.3213	0.0281
81	38860	Portland-South Portland-Biddeford, ME MSA	-2.3	23.1	0.0823	-0.5905	0.0565
68	39100	Poughkeepsie-Newburgh-Middletown, NY MSA	3.0	39.3	0.1681	-0.3412	0.0892
27	39300	Providence-New Bedford-Fall River, RI-MA MSA	-6.4	19.7	0.0632	-0.2811	0.0195
134	39340	Provo-Orem, UT MSA	12.8	34.8	0.2283	-0.3505	0.0946
112	39740	Reading, PA MSA	-2.5	32.3	0.0688	-0.2365	0.0621
141	39900	Reno-Sparks, NV MSA	3.1	36.1	0.1853	-0.5337	0.0665
43	40060	Richmond, VA MSA	-1.7	23.4	0.1226	-0.3075	0.0318
14	40140	Riverside-San Bernardino-Ontario, CA MSA	-4.1	28.3	0.0880	-0.5057	0.0317
137	40220	Roanoke, VA MSA	0.3	26.9	0.0693	-0.2453	0.0606
40	40380	Rochester, NY MSA	-3.9	16.7	0.0356	-0.1661	0.0215
128	40420	Rockford, IL MSA	-2.2	29.7	0.0625	-0.4521	0.0553
131	41420	Salem, OR MSA	-0.6	27.0	0.1192	-0.2798	0.0227
104	41500	Salinas, CA MSA	13.8	67.0	0.0486	-0.2828	0.0612
30	41700	San Antonio-New Braunfels, TX MSA	12.6	35.7	0.2708	-0.5189	0.3232
17	41740	San Diego-Carlsbad-San Marcos, CA MSA	2.4	34.8	0.3679	-0.4922	0.0676
11	41860	San Francisco-Oakland-Fremont, CA MSA	0.4	26.7	0.0982	-0.4089	0.0895
26	41940	San Jose-Sunnyvale-Santa Clara, CA MSA	16.1	69.7	0.0595	-0.2923	0.0587
98	42060	Santa Barbara-Santa Maria-Goleta, CA MSA	7.7	57.5	0.2565	-0.5426	0.2698
93	42220	Santa Rosa-Petaluma, CA MSA	-2.5	33.9	0.1543	-0.3119	0.2294
140	42340	Savannah, GA MSA	4.9	32.3	0.0888	-0.2679	0.0920
67	42540	Scranton–Wilkes-Barre, PA MSA	2.7	35.5	0.2243	-0.3379	0.0636
15	42660	Seattle-Tacoma-Bellevue, WA MSA	1.1	23.8	0.1252	-0.3690	0.1014
124	43780	South Bend-Mishawaka, IN-MI MSA	1.2	30.3	0.0798	-0.3608	0.0373
101	44060	Spokane, WA MSA	9.7	40.5	0.0872	-0.3621	0.0716
55	44140	Springfield, MA MSA	-6.4	22.2	0.2070	-0.3771	0.1364
122	44180	Springfield, MO MSA	5.7	35.8	0.0682	-0.2906	0.0275
13	41180	St. Louis, MO-IL MSA	-1.7	20.7	0.1585	-0.4339	0.0743

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Rank	CBSA	MSA	Mean	SD	μ_0	μ_1	σ^2
77	44700	Stockton, CA MSA	1.4	35.2	0.1372	-0.5472	0.0699
59	45060	Syracuse, NY MSA	2.3	34.5	0.2051	-0.3825	0.0716
22	45300	Tampa-St. Petersburg-Clearwater, FL MSA	-0.6	23.9	0.0749	-0.4303	0.0290
61	45780	Toledo, OH MSA	0.5	33.5	0.1111	-0.2862	0.0710
115	45940	Trenton-Ewing, NJ MSA	10.1	56.1	0.3127	-0.5096	0.1905
58	46060	Tucson, AZ MSA	2.0	29.9	0.1805	-0.3271	0.0633
50	46140	Tulsa, OK MSA	6.8	26.1	0.2029	-0.2604	0.0435
110	46700	Vallejo-Fairfield, CA MSA	5.7	50.3	0.2025	-0.3635	0.1619
28	47260	Virginia Beach-Norfolk-Newport News, VA-NC MSA	-1.3	17.8	0.0914	-0.2103	0.0198
118	47300	Visalia-Porterville, CA MSA	-2.1	22.0	0.0465	-0.2615	0.0357
7	47900	Washington-Arlington-Alexandria, DC-VA-MD-WV MSA	-0.3	20.7	0.0626	-0.3376	0.0238
74	48620	Wichita, KS MSA	1.6	26.9	0.1108	-0.3108	0.0527
52	49340	Worcester, MA MSA	2.3	38.9	0.2142	-0.4512	0.0739
111	49620	York-Hanover, PA MSA	-2.1	23.4	0.0757	-0.2639	0.0371
64	49660	Youngstown-Warren-Boardman, OH-PA MSA	-3.2	25.6	0.0373	-0.2711	0.0524

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