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The economic performance of cities: A Markov-switching approach ☆

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ABSTRACT

This paper examines the determinants of employment growth in metro areas. To obtain growth rates, we use a Markov-switching model that separates a city's growth path into two distinct phases (high and low), each with its own growth rate. The simple average growth rate over some period is, therefore, the weighted average of the high-phase and low-phase growth rates, with the weight being the frequency of the two phases. We estimate the effects of a variety of factors separately for the high-phase and low-phase growth rates. Growth in the high phase is related to both human capital and industry mix, while growth in the low phase is related to industry mix only, specifically, the relative importance of manufacturing. Overall, our results strongly reject the notion that city-level characteristics influence employment growth equally across the phases of the business cycle.

1. Introduction

Over the last two decades, a large empirical literature has focused on determining the characteristics associated with the growth of cities and other local markets (e.g., counties, metropolitan areas). Much of this work undoubtedly follows from the resurgence of growth theory and the corresponding empirical literature on cross-country growth. Because cities within the same country represent a rich cross section of economies with relatively similar cultural and institutional characteristics, they constitute an attractive sample that can be used to test growth theories. Moreover, given that the majority of the economic activity of the United States is located within urban areas, the growth of cities is also potentially important from the perspective of understanding aggregate US economic performance.

Whereas most studies of urban growth distinguish themselves by suggesting new explanatory variables, our contribution is a new approach for summarizing the economic performance of cities, which has usually focused on some measure of average growth over a given period. Our alternative is the Markov-switching approach of Hamilton (1989), in which an economy's growth path is characterized as having two distinct phases (high and low), each with its own growth rate. Instead of there being one underlying structure to the economy—as summarized by the average growth rate—the Markov-switching approach allows for two underlying structures that the economy switches between. This approach is used frequently in analyses of national-level recession and expansion phases, and has been applied to state-level data by Owyang et al. (2005).

To date, the Markov-switching approach has not been applied to city-level data, nor has it been used for serious analyses of growth. The approach is potentially useful, however, because the mechanisms that drive growth during a high phase may be very different from those driving it during a low phase.[1] By applying the Markov-switching approach to cities we hope to demonstrate first that city growth paths can be divided into high- and low-growth phases, and then that growth rates in the two phases are not related to the same variables. Low-growth phases occur because of shocks that throw a city's economy out of its steady state, which is when the economy is in its high-growth phase. Following these shocks—which can be national shocks to oil prices, productivity, monetary policy, etc., or more-localized shocks—an economy's performance is, in large part, a recovery toward the steady state. Because models of growth, whether at the national or city level, are models of the steady state, there is very little theory about the determinants of growth during low phases. There is no reason, therefore, to expect that the factors that we think are important for growth during the high phase will be the same as for growth during the low phase.

Indeed, recent research has documented the existence of various asymmetries between the growth and decline of local

☆ The views expressed are those of the authors and do not necessarily represent official positions of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

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[1] This was suggested in Owyang et al. (2005), although they looked at states, which are not the appropriate level of disaggregation for analyzing labor-market performance.

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labor markets. Glaeser and Gyourko (2005), for example, demonstrate that the distribution of population growth rates across US metropolitan areas tends to be "right-skewed": the highest growth rates are very large, whereas the lowest are relatively modest in magnitude. This result suggests that the estimated relationships between city-level characteristics and urban growth may depend on whether a city is expanding or contracting. In addition, work by Genesove and Mayer (2001) and Engelhardt (2003) shows that individuals tend to behave very differently during housing market booms and busts, further suggesting the existence of important differences across local market growth phases.

For the most part, studies of growth in cities have taken two approaches. This paper follows the first strand of the urban growth literature, although our analysis is informed by the second strand. In the first, the primary object of interest is some measure of growth that characterizes the entire local market (e.g., population, employment, aggregate income, per capita income). Typically, these studies estimate a series of regressions in an effort to identify which local market-level characteristics correlate significantly with one or more of these measures. Besides geographic differences (i.e., the rapid growth of the South and the West), much of this work has stressed the importance of human capital as a critical driver of growth over periods of several decades (Glaeser et al., 1995; Simon and Nardinelli, 2002; Glaeser, 2005a).

The second approach looks at growth patterns of specific city-industries rather than entire cities. Doing so simply acknowledges that the determinants of city-level growth may be very different for different types of employers. Hence, what drives growth within the construction industry may be very different from what drives growth among law firms. Much of this literature has focused on the importance of industrial diversity—as opposed to industrial concentration—and the role of human capital. Glaeser et al. (1992) find that cities with diverse industrial compositions tend to experience faster growth among their dominant industries (i.e., those with the most employment), while Henderson (1997) finds evidence that the concentration of a particular industry tends to promote its own growth, at least among capital-good-producing sectors (e.g., machinery, primary metals, transport equipment, electronics, instruments). Simon (2004) offers evidence that human capital is an important growth determinant, especially among skill-intensive industries (e.g., business services).

Our results reveal that studies that use overall average measures of performance mask a number of interesting differences between city-level growth phases in their relationships with perceived growth determinants. Most notably, human capital plays a significant role in driving growth during high phases, but not during low phases. Metropolitan areas with abundant quantities of skilled individuals seem to grow faster during their high phases, but fare no better than human-capital-scarce metropolitan areas during their low phases. We also find that the well-documented negative correlation between manufacturing and job growth is much stronger during low phases. Overall, our results strongly reject the notion that city-level characteristics influence employment growth equally across both phases of the business cycle.

The remainder of the paper proceeds as follows: The data set of city-level employment growth is described in Section 2. In Section 3 we describe and motivate the specification of the Markov-switching model used in our analyses. Section 4 describes our estimates of high-phase and low-phase growth rates for the cities in our sample, while Section 5 describes results relating high-phase and low-phase growth rates to hypothesized growth determinants. Section 6 concludes.

2. Data

Our data are from the Current Employment Statistics (or "payroll") survey of the Bureau of Labor Statistics (BLS). These data report quarterly estimates of total non-farm employment for all metropolitan areas in the country.[2] We restrict the sample to those with at least 200,000 in total employment as of the end of the sample period. Although we have no reason to believe that smaller cities do not exhibit the characteristics of Markov-switching, measures of employment for small cities can be extremely volatile due to measurement error and/or outliers. From this sample of 116 metropolitan areas, we eliminate two, Westchester County, NY, and Camden, NJ, because the geographic definitions we employ include the former as part of the New York metropolitan area and the latter as part of the Philadelphia metropolitan area. Our final sample, therefore, consists of 114 metropolitan areas.

Our sample period is 1990–2002. The starting date of the sample is restricted by the oft-found result that the national economy underwent a structural break in the early 1980s (Stock and Watson, 2003; McConnell and Perez-Quiros, 2000; Kim and Nelson, 1999a). Further, as found by Owyang et al. (in press), the date at which the structural break occurred varies a great deal at the state level. In fact, they find that several states experienced their breaks in the late 1980s. To help ensure that our data cover only the post-break period, we begin our sample in 1990. Finally, the end of our sample period is determined by the availability of final, unrevisable data for metropolitan areas prior to the changes in metro area definitions imposed in 2004. Only through the end of 2002 do the data satisfy this requirement.

Employment growth varied a great deal across cities over our sample period. The average quarterly growth rate was 0.37 percent, with a standard deviation of 0.26. The slowest-growing metro area—Hartford, CT—saw its employment decline at an average rate of 0.16 percent per quarter, whereas the fastest-growing metro area—Las Vegas, NV–AZ—experienced average quarterly growth of 1.38 percent. Further evidence of this diversity is provided by Table 1, which lists the top and bottom ten performers, and Appendix A, which lists all cities. Not surprisingly, the top performers are located primarily in the Sun Belt while the bottom performers tend to be in the Northeast.

3. The Markov-switching model

As an alternative to using the simple average growth rates as a measure of cities' economic performance, we use the Hamilton (1989) Markov-switching model, which describes the economy as switching between business cycle phases (high and low), each with its own average growth rate. Formally, let the growth rate of employment in city n in quarter t, $y_{n,t}$, be described as follows:

$$y_{n,t} = \mu_{n,S_{n,t}} + \varepsilon_{n,t},$$
$$\varepsilon_{n,t} \sim \text{i.i.d. } N\big(0, \sigma^2_{\varepsilon,n}\big),$$
$$\mu_{n,S_{n,t}} = \mu_{n,0}(1 - S_{n,t}) + \mu_{n,1} S_{n,t}, \quad \mu_{n,1} < \mu_{n,0}, \tag{1}$$

where the growth rate of employment has mean $\mu_{n,S_{n,t}}$, and deviations from this mean growth rate are created by the stochastic disturbance $\varepsilon_{n,t}$. To capture the two business cycle phases, the mean growth rate in (1) is permitted to switch between a high and low value, where the switching is governed by a latent state variable, $S_{n,t} = \{0, 1\}$.

[2] Urban growth empirics often examine the growth of income, income per capita, or population rather than employment. Many of these quantities turn out to be positively associated with employment growth; hence, we believe that many of the inferences we draw here would extend to the growth of other quantities.

Table 1
Highest and lowest average growth rates

City	Average growth rate
Highest	
Las Vegas, NV–AZ	1.38
Boise City, ID	1.07
Austin–San Marcos, TX	1.05
Phoenix–Mesa, AZ	0.91
Riverside–San Bernardino, CA	0.85
Orlando, FL	0.81
Sarasota–Bradenton, FL	0.78
Raleigh–Durham–Chapel Hill, NC	0.75
West Palm Beach–Boca Raton, FL	0.74
Salt Lake City–Ogden, UT	0.74
Lowest	
Buffalo–Niagara Falls, NY	0.02
Youngstown–Warren, OH	0.01
New York, NY	0.005
New Haven–Meriden, CT	0.004
Jersey City, NJ	0.001
Stamford–Norwalk, CT	−0.003
Bergen–Passaic, NJ	−0.014
Springfield, MA	−0.02
Los Angeles–Long Beach, CA	−0.05
Hartford, CT	−0.16

Note: Growth rates are quarterly percentage changes.

When $S_{n,t}$ switches from 0 to 1, the growth rate of employment switches from $\mu_{n,0}$ to $\mu_{n,1}$. Since $\mu_{n,1} < \mu_{n,0}$, $S_{n,t}$ switches from 0 to 1 at times when employment activity switches from high-growth to low-growth states.[3] Because $S_{n,t}$ is unobserved, estimation of (1) requires restrictions on the probability process governing $S_{n,t}$; in this case, we assume that $S_{n,t}$ is a first-order two-state Markov chain. This means that any persistence in the state is completely summarized by the value of the state in the previous period. Under this assumption, the probability process driving $S_{n,t}$ is described by the transition probabilities

$\Pr[S_{n,t} = i \mid S_{n,t-1} = j] = p_{ij,n}$.[4]

Here we are interested not only in documenting estimates of the high- and low-phase growth rates, $\mu_{n,0}$ and $\mu_{n,1}$, but also in investigating the extent to which a set of variables commonly hypothesized to be determinants of growth are associated with the high- and low-phase growth rates. To do so, we augment (1) by modeling the growth rate of city n, $\mu_{n,S_{n,t}}$, using the following "growth regression":

$$\mu_{n,S_{n,t}} = \delta_{S_{n,t}} + X_n'\beta_{S_{n,t}} + \nu_{n,S_{n,t}},$$
$$\nu_{n,S_{n,t}} \sim N\big(0, \sigma^2_{\nu,S_{n,t}}\big), \tag{2}$$

where $\delta_{S_{n,t}}$ is an intercept, X_n is a vector of city-specific characteristics, and $\nu_{n,S_{n,t}}$ is a residual. Among the covariates we consider in X_n are some of the most commonly used in existing studies.[5]

The variables in X_n are: total resident population and population density, both expressed in logarithms; the fraction of the population 25 years of age or older with a high school diploma and the fraction with a bachelor's degree; fractions of the population that are non-white and foreign-born; shares of total employment accounted for by manufacturing, services, and finance, insurance, and real estate (FIRE); the percentage of the local labor force covered by union contracts; the logarithm of average establishment size, based on establishments from all non-government industries; an index of industrial diversity, described below; region dummies; and three variables characterizing a city's climate (average January temperature, average July temperature, and average annual precipitation).[6] Because the dependent variable in (2), $\mu_{n,S_{n,t}}$, is measured for the period 1990–2002, we take 1990 values of the covariates to avoid endogeneity.[7]

The rationale for considering each of these quantities is straightforward. The two scale variables—population and density—are meant to capture whether agglomeration effects on productivity translate into faster growth over time, or whether the diseconomies associated with city size (e.g., congestion, high wages, high rents) produce slower growth.[8] The high school, college, non-white, and foreign-born percentages are intended to isolate the effects of human capital, while the three industry shares account for the differential growth rates of certain sectors (especially manufacturing as opposed to services) in recent decades.[9] Union activity, of course, directly affects hiring and firing decisions of employers, and so may influence employment growth.

We include average establishment size to account for the influence of the plant-size distribution on growth. Glaeser et al. (1992) and Rosenthal and Strange (2003), for example, have found that a larger presence of small plants, which is presumably associated with greater competition, has a positive effect on the growth of specific industries. In addition, because previous work has stressed the importance of industrial diversity (i.e., "Jacobs externalities") in driving economic growth (e.g., Glaeser et al., 1992), we include a measure of heterogeneity in the analysis. We quantify diversity using the following "Dixit–Stiglitz" index, based upon 4-digit employment data from County Business Patterns:

$$Diversity_n = \left(\sum_{i=1}^{I}\left(\frac{Emp_{in}}{Emp_n}\right)^{0.5}\right)^2, \tag{3}$$

where I is the total number of industries in the city, Emp_{in} is employment in industry i in city n, and Emp_n is total city employment. By construction, larger values of the index represent greater industrial heterogeneity.

[3] This identifying restriction is necessary for normalization, as without this restriction one can always reverse the definition of the state variable and obtain an equivalent description of the data.

[4] The model in (1) could be complicated on various dimensions, such as allowing for autoregressive dynamics, which might improve the model's fit of the data. We focus on the simple shifting-mean model in (1) because our goal is to date regime shifts between high and low phases. More highly parameterized models would be useful if our goal were instead to determine whether the data generating process for the city-level data was linear or nonlinear, an interesting question that we do not address here.

[5] In constructing these city-level characteristics, we have to construct "approximations" to the metropolitan areas in New England because the BLS reports employment data for Metropolitan Statistical Areas (a non-county-based geography) rather than New England County Metropolitan Areas. A brief description of our approximation procedure appears in Appendix B.

[6] We construct metropolitan area characteristics from county-level observations using geographic definitions from 1993.

[7] Using 1980 values of the covariates did not significantly change our findings. Still, in spite of the lagged nature of our regressors, some may be concerned that various unobserved aspects of a metropolitan area (e.g., some amenity) may induce simultaneity between the regressors and the rate of growth. For example, aspects that lead to faster growth in a city may also induce highly educated workers to locate there, creating bias (positive) in the estimated coefficient on human capital. However, given that our primary aim is to estimate differences between how characteristics, such as human capital, relate to growth across high- and low-growth phases, we believe that this bias does not inhibit our ability to draw inferences on this matter. In particular, if the bias is similar in high-growth phases and in low-growth phases, the difference between the two coefficients will still accurately estimate the difference in the associations across the two states of the business cycle.

[8] It is worth noting that because our sample does not include smaller cities, our results for density and population might underestimate their effects.

[9] We include FIRE in addition to manufacturing and services because the growth of some cities during the 1990s may have been especially influenced by this broad sector. Glaeser (2005a, 2005b), for example, suggests that the growth of Boston and New York in recent decades has been strongly tied to finance and business services.

Finally, given that there has been such strong regional variation in city-level growth in the past half century, we attempt to control for these effects with region dummies and climate features. Climate, of course, represents a potentially important amenity driving growth (e.g., Glaeser et al., 2001).[10]

To estimate the parameters of the model in (1) and (2), as well as draw inference regarding the unobserved $S_{n,t}$, we take a Bayesian approach. The Bayesian approach has a number of features that make it attractive for estimation of Markov-switching models, with a primary example being the ability to easily incorporate uncertainty about model parameters into inference regarding $S_{n,t}$. Bayesian estimation produces a posterior distribution for the model parameters, which can be used to extract point estimates and measures of dispersion. To evaluate the evidence in favor of each of the hypothesized growth determinants in X_n, we use Bayesian posterior model probabilities to compare restricted and unrestricted versions of the growth equation in (2). In particular, denote M_U as the model in (1) and (2) with the full set of growth determinants in X_n included, and M_R as the model in (1) and (2) with all but one element of X_n included. We then construct the ratio of posterior model probabilities, or posterior odds ratio:

$$P_{UR} = \frac{\Pr(M_U \mid Y)}{\Pr(M_R \mid Y)}, \tag{4}$$

where Y denotes the full set of data used to estimate the model. Values of P_{UR} greater than unity suggest that the unrestricted model has higher posterior probability than the restricted model, and is evidence in favor of the inclusion of the elements of X_n that were omitted from the restricted model. Appendix C provides details regarding the Bayesian estimation of the model in (1) and (2) as well as the methods used to construct the posterior odds ratios.

4. Estimates of high- and low-phase growth rates

4.1. Results for selected cities

To illustrate how the Markov-switching model separates cities' growth paths into high and low phases, consider six cities that are roughly representative of the sample: New York, NY; Phoenix–Mesa, AZ; Cleveland–Lorain–Elyria, OH; Sacramento, CA; Albany–Schenectady–Troy, NY; and Mobile, AL. The quarterly growth rate series for these cities are provided in Fig. 1, which also shows point estimates of the high-phase and low-phase growth rates, $\mu_{n,0}$ and $\mu_{n,1}$.[11]

The wide variety of city-level experiences is readily apparent from the figures. First, the cities differ a great deal in the levels of and the spread between their high-phase and low-phase growth rates. New York, for example, experienced relatively modest growth during high phases and suffered deep low phases.[12] Phoenix–Mesa had the opposite experience: its high-phase growth rate was more than three times that of New York, and its low-phase growth rate was nearly as high as New York's high-phase growth rate. In fact, because the level of employment in Phoenix–Mesa (and several other cities) tends not to recede, even during its low phase, we cannot refer generally to city-level low phases as "recessions," as is done when describing the national business cycle.

The growth experiences of the other four cities were less extreme than for New York and Phoenix–Mesa, but also demonstrate the variety of estimated high-phase and low-phase growth rates: While the high phases in Cleveland–Lorain–Elyria were more robust than in New York, its low phases were not as deep, although they were noticeably deeper than they were for the other four cities. Sacramento saw faster growth than Cleveland in both phases, as did Albany–Schenectady–Troy, although, for the latter, the difference between the phases was relatively small. Mobile was the most average of these six cities, with high-phase and low-phase growth rates close to the means across our sample cities.

Along with the two phase growth rates, overall economic performance depends on the relative occurrence of the two phases. Put simply, the model determines the probability that a city is in the low phase for any time period by comparing the actual growth rate to the two phase growth rates, while also accounting for the persistence of the series. The estimated low-phase probability for the six cities is provided by Fig. 2. For reference, the panels include shaded areas to indicate periods of national recession as determined by the National Bureau of Economic Research (NBER) Business Cycle Dating Committee, of which there were two: Q3.1990 to Q1.1991 and Q1.2001 to Q4.2001. From the figure it is clear that the model is able to differentiate easily between the two phases in that the low-phase probabilities tend to shift sharply between values close to zero and one.

There were significant differences in both the frequency and timing of city-level low phases. New York's low phase lasted more than a year beyond the end of the 1990–1991 NBER recession, although its 2001 low phase was relatively in synch with the 2001 NBER recession. The opposite occurred for Cleveland–Lorain–Elyria, which experienced a short low phase in 1990–1991 and a long one in 2000–2002. In contrast, both low phases in Phoenix–Mesa began earlier and ended later than NBER recessions.

Some cities either did not have low phases during periods of national recession or had low phases of their own that were not widespread across the nation. Sacramento, for example, did not even enter its low phase until after the 1990–1991 NBER recession had ended, and the city completely missed the 2001 recession. Mobile, on the other hand, missed the first national recession but saw the second. Albany–Schenectady–Troy had the worst luck of the six cities in that it was hit by the two NBER recessions and an idiosyncratic low phase in 1995–1996.

4.2. Results for all cities

A few summary statistics describing the estimated growth rates within each of the two phases, along with overall average rates of growth, appear in Table 2. The entire set of results for our 114 cities is provided by Appendix A. From Table 2, we can see that

Table 2
Summary statistics for city-level business cycle phases

Variable	Mean	Standard deviation	Minimum	Maximum
Average growth rate	0.37	0.26	−0.16	1.38
High-phase growth rate	0.62	0.27	0.12	1.49
Low-phase growth rate	−0.33	0.34	−1.45	0.56
Fraction of time in low phase	0.27	0.09	0.12	0.70
Switches into low phase	1.91	0.74	1	4

Note: Statistics calculated across 114 metropolitan areas. Growth rates represent quarterly percentage changes.

[10] Although regional indicators should pick up some of the variation in climate across metropolitan areas throughout the United States (the South is, after all, warmer than the Northeast on average), they do so only incompletely because regions tend to be extremely large. For example, Seattle, WA, and Phoenix, AZ, are both located in the West region. Seattle averages 40 degrees in January, 65.2 degrees in July, and 37.19 inches of precipitation. Phoenix averages 53.6 degrees in January, 93.5 degrees in July, and 7.66 inches of precipitation.

[11] As our point estimate, we use the mean value of the Bayesian posterior distribution.

[12] Note that our results are not driven by single-quarter spikes in employment growth such as the one for New York following the September 11, 2001, terror attacks. The model takes account of persistence, and one-quarter shocks like that for New York in Q4.2001 are treated as stochastic occurrences, as in Eq. (1).

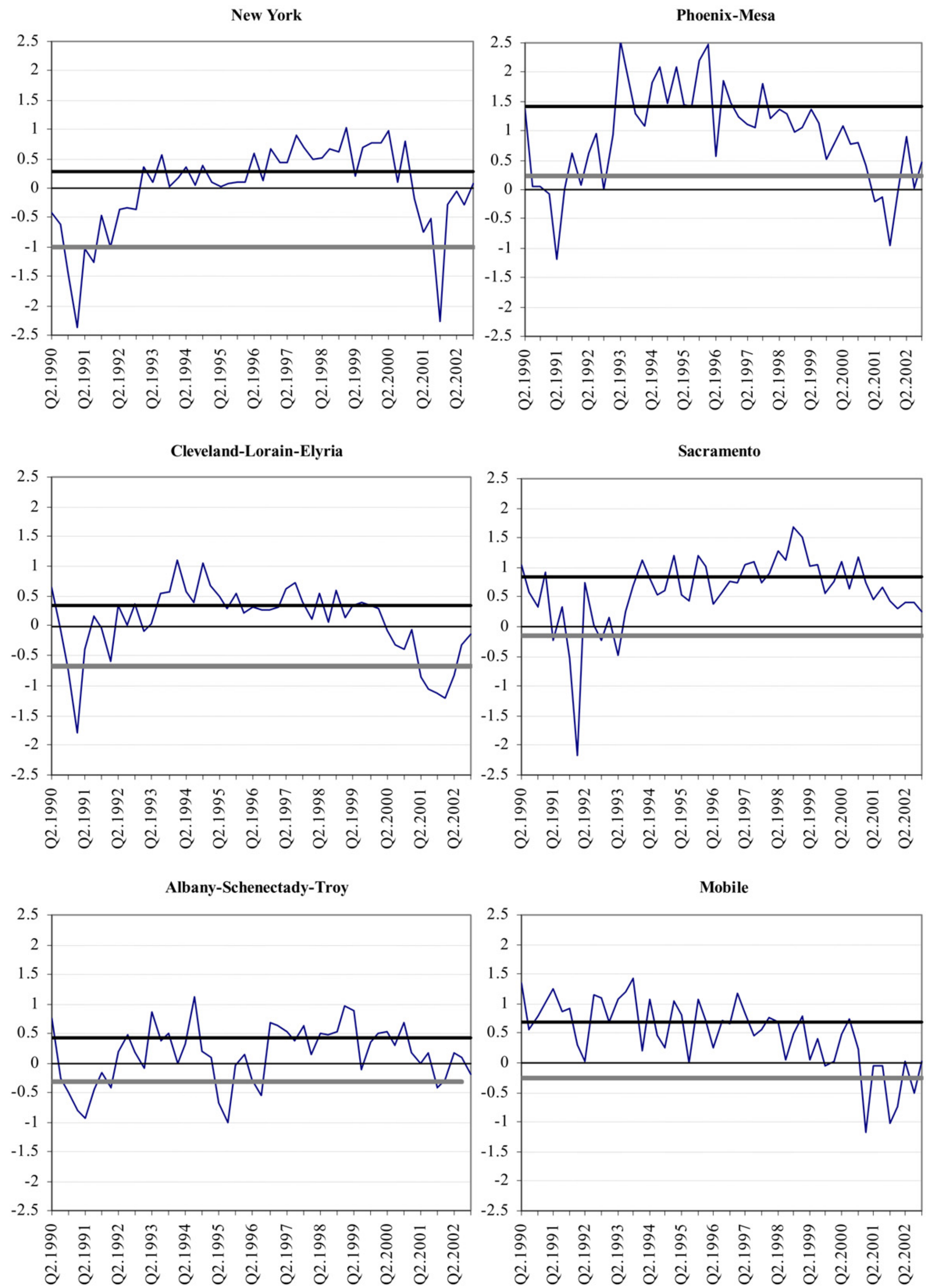

Fig. 1. Employment growth rates for selected cities. *Note:* Thick black (gray) line is estimated high-phase (low-phase) growth rate.

while low phases are indeed periods of slower employment growth than are high phases—the average estimated low-phase growth rate is −0.33 percent per quarter and the average estimated high-phase growth rate is 0.62 percent—there is a fair amount of variation within the sample. Low-phase growth rates range from −1.45 percent to 0.56 percent; high-phase rates extend from 0.12 percent to 1.49 percent.

Although cities did tend to experience decreases in their employment levels during low phases, some actually continued to grow during them, as described above for Phoenix–Mesa. This

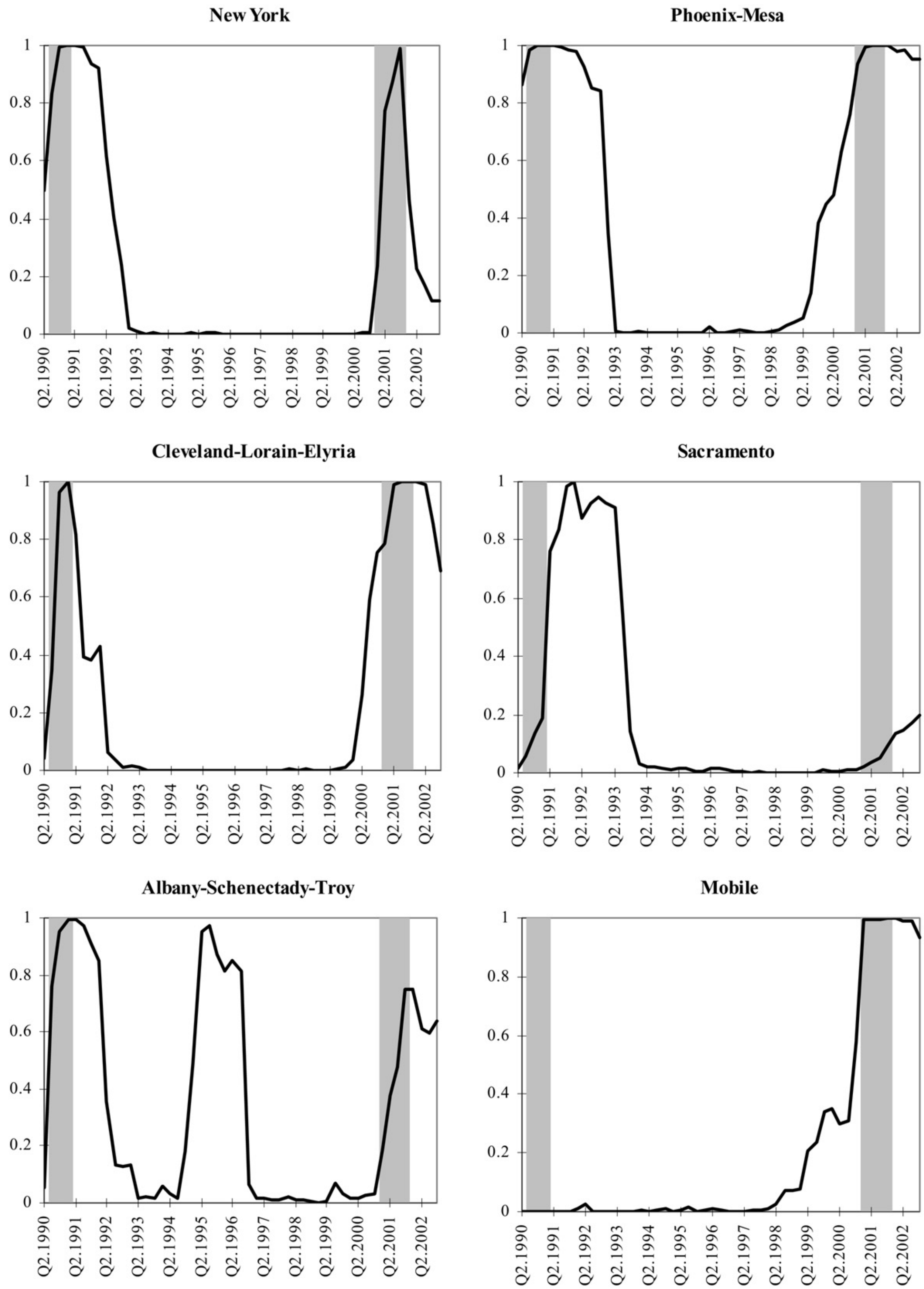

Fig. 2. Low-phase probabilities for selected cities. *Note:* Gray shaded areas indicate national NBER recessions.

result can also be seen in Table 3, which identifies the cities with the highest and lowest estimated growth rates in each business cycle phase. Metropolitan areas located in the South and the West, not surprisingly, tended to have had the highest rates of growth across both phases. Las Vegas, for instance, had the highest high-phase growth rate, 1.49 percent, as well as the highest low-phase growth rate, 0.56 percent. The slowest growers in either phase, on the other hand, tended to be located in states lying within the northeastern quadrant of the country, such as New York, New Jersey, Massachusetts, Connecticut, and Ohio, although some cities in

Table 3
Highest and lowest growth rates by business cycle phase

City	High-phase growth rate	City	Low-phase growth rate
Highest		**Highest**	
Las Vegas, NV–AZ	1.49	Las Vegas, NV–AZ	0.56
Phoenix–Mesa, AZ	1.42	Albuquerque, NM	0.26
Austin–San Marcos, TX	1.30	Riverside–San Bernardino, CA	0.25
Boise City, ID	1.22	Phoenix–Mesa, AZ	0.23
Albuquerque, NM	1.12	Tucson, AZ	0.20
Orlando, FL	1.09	Fresno, CA	0.19
Riverside–San Bernardino, CA	1.05	San Antonio, TX	0.19
Tucson, AZ	1.02	Charleston–North Charleston, SC	0.06
Atlanta, GA	1.02	Houston, TX	0.05
Tampa–St Petersburg–Clearwater, FL	0.99	Reno, NV	0.04
Lowest		**Lowest**	
Scranton–Wilkes–Barre–Hazelton, PA	0.27	San Francisco, CA	−0.84
New Haven–Meriden, CT	0.26	New Haven–Meriden, CT	−0.87
Newark, NJ	0.26	Providence–Fall River–Warwick, RI–MA	−0.90
Bergen–Passaic, NJ	0.25	Boston, MA–NH	−0.92
Youngstown–Warren, OH	0.25	Stamford–Norwalk, CT	−0.95
Gary, IN	0.23	Bergen–Passaic, NJ	−0.96
Rochester, NY	0.21	New York, NY	−1.01
Syracuse, NY	0.21	Jersey City, NJ	−1.07
Buffalo–Niagara Falls, NY	0.16	Worcester, MA–CT	−1.20
Hartford, CT	0.12	San Jose, CA	−1.45

Note: Growth rates represent quarterly percentage changes.

the South and the West (e.g., San Francisco and San Jose) had relatively poor performance during their low phases.[13]

There is a fair amount of overlap between the two sets of phase growth rates. Cities that grew the fastest during their high phases also tended to grow fastest during their low phases. This can be seen more formally from the correlation between the two sets of estimated growth rates across the 114 cities in the sample: 0.60. There is also some overlap with overall rates of growth. The correlation between low-phase growth rates and overall average growth is 0.70; the correlation between high-phase growth rates and overall average growth is 0.93.

Table 2 also records a statistic measuring the frequency of the low-growth phase, namely the expected value that $S_{n,t} = 1$ over the sample period. Summary statistics for this expected value appear in the second-to-last row of Table 2.[14] On average, the metropolitan areas in the sample spent approximately 27 percent of the time in a low phase.[15] Yet, as indicated by the standard deviation of 0.09, there is good deal of variation within the sample. One metropolitan area, Philadelphia, PA, spent only 12 percent of the time in its low phase, whereas Honolulu, HI, was in its low phase 70 percent of the time. There were some regional differences in the frequency of the low phase, as cities in the West tended to have experienced the low phase more frequently while cities in the Northeast experienced it less frequently.[16]

More information about the top and bottom of the distribution of low-phase frequencies can be gathered from Table 4, which reports the cities with the 10 highest and lowest frequencies. One important result is that low average growth rates were not typically driven by the frequency of the low phase. Overall, the correlation between average growth and low-phase frequency is −0.01. This lack of a pattern is highlighted by the table. Some of the metropolitan areas behaved just as one might expect, at least in the sense that some cities with particularly high rates of average growth (e.g., Austin–San Marcos, TX, and Boise, ID) spent relatively little time in the low phase, whereas some slow growers (e.g., Honolulu, HI) spent a large fraction of time in the low phase. Yet, there are a number of results that are somewhat surprising. Fast growers like Phoenix–Mesa, AZ, and Albuquerque, NM, actually spent relatively long periods of time in the low phase (respectively, 43 percent and 63 percent). On the other hand, some slow growers, including Philadelphia, PA, and Worcester, MA–CT, spent relatively

Table 4
Highest and lowest low-phase frequencies

City	Fraction of time in low phase
Highest	
Honolulu, HI	0.70
Albuquerque, NM	0.63
Bakersfield, CA	0.48
Ventura, CA	0.48
San Diego, CA	0.46
Charleston–North Charleston, SC	0.44
Phoenix–Mesa, AZ	0.43
Tucson, AZ	0.43
Orange County, CA	0.41
Oakland, CA	0.41
Lowest	
Tulsa, OK	0.17
Worcester, MA-CT	0.16
Providence–Fall River–Warwick, RI–MA	0.16
Appleton–Oshkosh–Neenah, WI	0.16
Denver, CO	0.16
Austin–San Marcos, TX	0.16
Kalamazoo–Battle Creek, MI	0.16
Madison, WI	0.16
Boise City, ID	0.15
Philadelphia, PA–NJ	0.12

Note: Figures represent the proportion of the 1990–2002 period spent in a low phase.

[13] The average low-phase growth rates by region are: Northeast, −0.66; Midwest, −0.33; South, −0.16; West, −0.22. The average high-phase growth rates by region are: Northeast, 0.34; Midwest, 0.49; South, 0.83; West, 0.87.

[14] The low-phase frequencies for all cities are in the second-to-last column in the table in Appendix A.

[15] In contrast, according to the NBER, the national economy was in recession 13.5 percent of the time. There was a significant divergence, however, between official recessions and periods of negative employment growth at the national level. Applying the Markov-switching model without the growth equation to national data indicates that the United States was in an employment recession for 35 percent of the sample period.

[16] The low-phase frequencies by region are: Northeast, 0.23; Midwest, 0.26; South, 0.27; West 0.34.

little time in their low phase (respectively, 12 percent and 16 percent).[17]

As illustrated by Fig. 2, cities tended to switch infrequently from one phase to another and then to stay in their new phase for at least several quarters.[18] Also, although there was a tendency for cities to have experienced their low phases around the periods when the national economy was in recession, there was a great deal of variation. Some cities did not switch at all around national recessions, whereas other cities switched into their low phases even though the overall economy was expanding. The variety of experiences is summarized by the last row of Table 2: Cities switched into their low phases an average of 1.9 times during the sample period, slightly less frequently than did the national economy. There were 31 cities that switched only once into their low phase, and five—Augusta, GA; Johnson City, TN; Tucson, AZ; Ventura, CA; and Wichita, KS—that switched four times.[19]

5. Estimates of growth regressions

In this section we describe the estimated coefficients on the hypothesized growth determinants included in the growth regression in (2), as well as the statistical evidence in support of each growth determinant. As a means of comparison, we first estimate a version of (1) and (2) in which the high- and low-phase growth rates are assumed to be equal, so that $\mu_{n,0} = \mu_{n,1}$. With this restriction there is no regime switching between high- and low-phase growth rates, and the model in (1) and (2) collapses to a simple growth regression applied to average growth rates, a specification that forms the basis of the extant literature on the determinants (or, at least, correlates) of economic growth in cities. With results for this baseline model in hand, we then present results for the full Markov-switching model, which enables us to investigate how the growth determinants influence high- and low-phase growth rates separately.

5.1. Results for average growth rates

Table 5 presents the estimated coefficients of the growth regression in (2) for the model without Markov-switching, so that the growth determinants are used to explain average growth rates. The first column of Table 5 reports the mean of the Bayesian posterior distribution for each of these coefficients, which serves as our point estimate, while the second column reports the standard deviation of the posterior distribution. The final column holds the posterior odds ratio from (4), P_{UR}, comparing the model including all the growth determinants to a restricted model in which the growth determinant in that row is eliminated. Again, values of $P_{UR} > 1$ indicate that the data prefer the model that includes the growth determinant. To facilitate discussion, but with a slight abuse of terminology, we refer to growth determinants for which $P_{UR} > 1$ as being "statistically significant."

Table 5
Growth determinants and average growth rates

	Posterior mean	Posterior Std. Dev.	Posterior odds
Log density	−0.025	0.039	0.02
Log population	0.004	0.062	0.03
% High school	0.026	0.938	0.42
% College	0.844	0.696	0.67
% Non-white	−1.135	0.306	365.50
% Foreign-born	−0.280	0.478	0.26
% Manufacturing	−1.305	0.605	2.79
% Services	−0.654	0.723	0.49
% FIRE	−0.673	1.101	0.61
% Union coverage	−0.249	0.566	0.29
Industrial diversity	−0.0001	0.001	0.00
Log avg. plant size	0.166	0.244	0.14
Avg. January temp.	0.003	0.004	0.00
Avg. July temp.	0.017	0.007	0.10
Annual precipitation	−0.002	0.003	0.00
Northeast region	−0.208	0.121	0.23
Midwest region	−0.081	0.109	0.06
West region	0.103	0.141	0.08

The results in Table 5 demonstrate a number of patterns that have already been well documented. Beginning with the variables meant to measure human capital, both education variables produce a positive coefficient, a result that is generally interpreted as suggesting that higher levels of human capital are associated with faster rates of employment growth. However, neither variable is deemed statistically significant by the posterior odds ratio.[20] The fraction of a metropolitan area's resident population that is non-white generates a strongly significant negative coefficient, which may also reflect a human capital effect. In particular, racial minorities may possess lower levels of human capital for reasons that differ from lower levels of education per se, such as less work experience due to greater instability in their job histories.

Among the three industry shares and the three local labor-market characteristics (unionization, industrial diversity, and average plant size), only the manufacturing share is significantly associated with average employment growth. Larger fractions of employment initially engaged in manufacturing tend to be accompanied by lower rates of growth subsequently, which is quite reasonable in light of the decline in manufacturing employment over the last several decades.

None of the estimated region and climate coefficients are statistically significant. In terms of point estimates, we see that cities with higher January and July temperatures and lower precipitation exhibited faster growth, and that metropolitan areas in the South and West grew faster than those in either the Midwest or the Northeast.[21] In terms of their signs, these results are quite standard.

We find little association between growth and either of our scale measures. Hence, while large, dense urban areas tend to be characterized by higher productivity, they do not grow faster than smaller markets. There is also little evidence that employment growth is associated with the presence of foreign-born individuals or high rates of unionization, at least after accounting for industrial composition and geographic effects. We see little association between growth and FIRE's share of total employment, suggesting that, although this sector may have helped underlie the success

[17] We should note that for a small number of cities our model does not do as good a job in separating the business cycle into two distinct phases as it did for the six sample cities. The experience of Philadelphia, for example, is probably more appropriately described as having three phases. The downturn in the early 1990s was so deep that the model characterizes the much shallower downturn of 2000–2001 as being in the high phase, which accounts for the infrequency of the low phase for Philadelphia. Put another way, it is likely that a three-phase model would characterize the early 1990s period as a medium phase. Presently, however, we are not particularly interested in fit and, because we have no reason to believe that any error of this sort is related to any of our explanatory variables, our findings should not be biased as a result.

[18] Following convention, an economy is in a low phase when its probability of a low phase is at least 50 percent.

[19] The last column of Appendix A reports the number of switches that were experienced by each city.

[20] An earlier version of this paper estimates the model in two stages—Markov-switching and then growth regressions—and finds stronger support for the role of human capital. Specifically, the coefficients on the share with a college degree and the percent non-white are both statistically significant and have the expected signs. See Owyang et al. (2007).

[21] Mean average growth rates across metropolitan areas by region are: Northeast, 0.11; Midwest, 0.29; South, 0.49; West, 0.54.

of some cities in the United States (e.g., Boston and New York—see Glaeser, 2005a, 2005b) in recent decades, it did not impart a boost to all cities during the 1990–2002 period. There is also little association between our index of industrial diversity and growth. As such, we do not find any evidence of Jacobs externalities on overall metropolitan area-level employment growth. In addition, employment growth is not significantly tied to average establishment size. Both of these results stand somewhat at odds with the findings of Glaeser et al. (1992), who find that industries in cities with diverse economies and relatively small firms grow faster.[22]

5.2. *Results for high- and low-phase growth rates*

We now turn to estimates of the coefficients of the growth regression in (2) obtained from the model with Markov-switching between high- and low-phase growth rates. Table 6 presents the coefficient estimates and measures of statistical significance for the high-phase growth rates, while Table 7 presents these measures for the low-phase growth rates.

Beginning with Table 6, several of the results look similar to those derived from the average growth rates (Table 5). For example, the non-white fraction and manufacturing share each again produce significantly negative coefficients. There are, however, some differences between these findings and those for the average growth rates in Table 5. Most notably, the coefficient on the college fraction is deemed to be statistically significant for the high-phase growth rates, whereas it was insignificant for the average growth rates. The point estimate for this coefficient is also substantially larger for the high-phase growth rates than it was for average growth rates. This result suggests that education, and more generally human capital, may be more important in high-growth phases than it is for overall growth.

As noted above, much of the urban literature has argued that small firms tend to be associated with faster growth because they enhance competition and, thus, productivity over time. We found no significant relationship between average plant size and average growth, and this is confirmed when we consider only high-phase growth rates. Interestingly, the coefficient for high-phase growth remains positive and is *larger* than it was for average growth, which moves the estimated relation between growth and establishment size further from the negative relationship argued for in much of the existing literature.

Turning to the results for the low-phase growth rates in Table 7, we see a different set of significant coefficients than we found for the high-phase growth rates. In particular, neither the college fraction nor the non-white percentage of the population is significant. If we, once again, interpret these variables as measuring the human capital of the local population, these findings offer little evidence that human-capital-abundant metropolitan areas experience milder low phases than human-capital-poor ones. This result is somewhat surprising because highly educated workers tend to experience lower rates of job displacement and unemployment than less-educated workers.[23] Hence, one might expect to see fewer job losses (i.e., higher employment growth) in highly educated cities than in less-educated cities. We find little support for this idea.

The variable that offers the strongest association with low-phase growth is the manufacturing share of total employment. The estimated coefficient is significant, and suggests that a 10-percentage-point rise in manufacturing's share of total employment corresponds to a 0.24-percentage-point decrease in the rate of growth that a city experiences while in the low phase. Recall that, although we also found a negative association between manufacturing and high-phase growth, it was much weaker: on the order of one half as high. Therefore, manufacturing's well-established drag on employment growth is much stronger during low phases than during high phases.

Table 6
Growth determinants and high-phase growth rates

	Posterior mean	Posterior Std. Dev.	Posterior odds
Log density	−0.009	0.044	0.02
Log population	−0.019	0.070	0.03
% High school	−0.198	1.040	0.47
% College	1.254	0.760	1.29
% Non-white	−1.058	0.376	9.03
% Foreign–born	−0.384	0.564	0.31
% Manufacturing	−1.187	0.679	1.39
% Services	−0.759	0.866	0.56
% FIRE	−0.540	1.240	0.61
% Union coverage	−0.496	0.660	0.39
Industrial diversity	0.0001	0.001	0.00
Log avg. plant size	0.292	0.300	0.22
Avg. January temp.	0.008	0.005	0.01
Avg. July temp.	0.017	0.008	0.04
Annual precipitation	−0.003	0.004	0.00
Northeast region	−0.127	0.142	0.09
Midwest region	−0.011	0.131	0.06
West region	0.170	0.157	0.12

Table 7
Growth determinants and low-phase growth rates

	Posterior mean	Posterior Std. Dev.	Posterior odds
Log density	−0.102	0.073	0.08
Log population	0.016	0.107	0.05
% High school	1.098	1.424	0.86
% College	−0.198	1.069	0.49
% Non-white	−0.002	0.542	0.24
% Foreign-born	−0.797	0.848	0.63
% Manufacturing	−2.361	0.950	9.65
% Services	−0.787	1.250	0.73
% FIRE	−0.397	1.653	0.74
% Union coverage	0.071	0.949	0.43
Industrial diversity	−0.0003	0.002	0.00
Log avg. plant size	0.181	0.450	0.21
Avg. January temp.	0.005	0.007	0.00
Avg. July temp.	0.008	0.011	0.01
Annual precipitation	−0.009	0.006	0.01
Northeast region	−0.195	0.215	0.14
Midwest region	−0.008	0.207	0.09
West region	−0.156	0.260	0.14

The region indicators and climate variables offer only limited explanatory power. Nevertheless, the point estimates from the region dummies may provide some interesting insights into geographic patterns of low-phase growth. For high-phase growth, the West region indicator yielded a positive coefficient. Although it is not significant, the West region indicator produces a negative coefficient for low-phase growth, suggesting that low phases might have been somewhat worse in western metropolitan areas than in the South.

As with all of the other results, we see no association between low-phase growth and either rates of union coverage or the extent of industrial diversity. This latter result suggests that while cities with more heterogeneous economies might experience lower rates of unemployment (e.g., Simon, 1988), their low phases are not milder in terms of higher rates of employment growth.

[22] The discrepancy between the two sets of results may emanate from the fact that Glaeser et al. (1992) look at employment growth within a city's largest industries rather than overall employment growth.

[23] Recent data on unemployment rates by educational attainment level are reported by the BLS at http://www.bls.gov/news.release/empsit.t04.htm.

6. Conclusions

This paper examined the determinants of employment growth in metro areas using a Markov-switching model to separate cities' growth paths into high and low phases, each with its own growth rate. We estimated the effects of a variety of factors separately for the average growth rate, the high-phase growth rate, and the low-phase growth rate, and found different sets of statistically significant variables across the three types of growth rates.

One characterization of our results is that the growth determinants used in the urban growth literature seem much better at explaining high-phase growth than low-phase growth. This might be seen as a Tolstoy theorem of urban growth: Happy cities are all alike; every unhappy city is unhappy in its own way.[24] Specifically, we found that growth in the high phase is related to several of the usual variables, including human capital, but that low-phase growth is related only to the relative importance of manufacturing. Also, the relative overall performance for cities—their average growth rates—are not correlated with the frequency with which they are in their low phase.

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[24] We thank Ed Coulson for suggesting this interpretation.

Appendix A

Average and phase growth rates and low-phase frequencies for all 114 cities

	Average growth rate	High-phase growth rate	Low-phase growth rate	Low-phase frequency	Switches into low phase
Akron OH PMSA	0.266	0.454	−0.248	0.289	2
Albany–Schenectady–Troy NY	0.158	0.414	−0.332	0.348	3
Albuquerque NM	0.603	1.123	0.262	0.626	2
Allentown–Bethlehem–Easton PA	0.251	0.431	−0.278	0.311	2
Ann Arbor MI PMSA	0.341	0.490	−0.485	0.223	2
Appleton–Oshkosh–Neenah WI	0.503	0.597	−0.152	0.160	1
Atlanta GA	0.693	1.016	−0.115	0.319	2
Augusta–Aiken GA–SC	0.198	0.435	−0.194	0.376	4
Austin–San Marcos TX	1.051	1.304	−0.402	0.158	1
Bakersfield CA	0.430	0.876	0.043	0.485	2
Baltimore MD PMSA	0.152	0.392	−0.488	0.261	2
Baton Rouge LA	0.526	0.728	−0.161	0.213	1
Bergen–Passaic NJ PMSA	−0.014	0.254	−0.960	0.216	1
Birmingham AL	0.372	0.556	−0.163	0.250	2
Boise City ID	1.069	1.219	−0.066	0.154	1
Boston MA–NH PMSA	0.094	0.519	−0.924	0.290	2
Buffalo–Niagara Falls NY	0.018	0.164	−0.632	0.185	2
Charleston–North Charleston SC	0.522	0.827	0.057	0.439	2
Charlotte–Gastonia–Rk Hill NC–SC	0.559	0.903	−0.286	0.309	2
Chattanooga TN–GA	0.317	0.588	−0.238	0.352	3
Chicago IL PMSA	0.212	0.419	−0.422	0.262	2
Cincinnati OH–KY–IN PMSA	0.284	0.480	−0.330	0.243	2
Cleveland–Lorain–Elyria OH PMSA	0.073	0.333	−0.665	0.261	2
Columbia SC	0.486	0.820	−0.357	0.280	2
Columbus OH	0.453	0.652	−0.263	0.222	2
Dallas TX PMSA	0.613	0.962	−0.382	0.259	2
Dayton–Springfield OH	0.034	0.282	−0.487	0.311	2
Denver CO PMSA	0.616	0.839	−0.485	0.158	1
Des Moines IA	0.433	0.643	0.011	0.330	2
Detroit MI PMSA	0.170	0.453	−0.587	0.292	2
El Paso TX	0.429	0.561	−0.152	0.201	2
Ft Lauderdale FL PMSA	0.641	0.836	−0.161	0.202	2
Fort Wayne IN	0.229	0.482	−0.425	0.270	2
Fort Worth–Arlington TX PMSA	0.565	0.869	−0.241	0.277	2
Fresno CA	0.564	0.693	0.194	0.310	1
Gary IN PMSA	0.133	0.230	−0.216	0.281	1
Gr Rapids–Muskegon–Holland MI	0.503	0.738	−0.405	0.249	2
Grnsboro–Winston–Salem–Hi Pt NC	0.304	0.562	−0.551	0.228	2
Grnville–Spartanb–Anderson SC	0.314	0.608	−0.713	0.200	2
Harrisburg–Lebanon–Carlisle PA	0.307	0.385	0.009	0.267	2
Hartford CT	−0.160	0.115	−0.794	0.242	1
Honolulu HI	0.068	0.607	−0.115	0.698	2
Houston TX PMSA	0.590	0.879	0.050	0.374	3
Indianapolis IN	0.426	0.584	−0.088	0.264	2
Jackson MS	0.425	0.638	0.027	0.369	2
Jacksonville FL	0.537	0.859	−0.092	0.334	2
Jersey City NJ PMSA	0.001	0.354	−1.069	0.267	3
Johnson City–Kingsp–Bris TN–VA	0.312	0.509	−0.250	0.293	4
Kalamazoo–Battle Creek MI	0.155	0.366	−0.823	0.156	2
Kansas City MO–KS	0.375	0.625	−0.342	0.253	2
Knoxville TN	0.563	0.680	0.007	0.229	1
Lancaster PA	0.321	0.425	−0.288	0.191	1

(*continued on next page*)

Appendix A (*continued*)

	Average growth rate	High-phase growth rate	Low-phase growth rate	Low-phase frequency	Switches into low phase
Lansing–East Lansing MI	0.222	0.376	−0.131	0.283	1
Las Vegas NV–AZ	1.375	1.493	0.559	0.297	2
Lexington KY	0.423	0.676	−0.413	0.222	1
Little Rock–N Little Rock AR	0.467	0.614	−0.066	0.225	2
LA–Long Beach CA PMSA	−0.050	0.384	−0.619	0.384	2
Louisville KY–IN	0.360	0.610	−0.511	0.220	2
Madison WI	0.623	0.690	0.001	0.155	1
Memphis TN–AR–MS	0.384	0.634	−0.097	0.366	2
Miami FL PMSA	0.269	0.553	−0.489	0.261	2
Mdlesex–Somerset–Hunterd NJ PMSA	0.323	0.605	−0.600	0.250	2
Milwaukee–Waukesha WI PMSA	0.219	0.399	−0.463	0.215	2
Minneapolis–St Paul MN–WI	0.428	0.608	−0.265	0.217	2
Mobile AL	0.506	0.692	−0.263	0.204	1
Monmouth–Ocean NJ PMSA	0.364	0.548	−0.579	0.173	1
Nashville TN	0.592	0.840	−0.195	0.256	2
Nassau–Suffolk NY PMSA	0.149	0.366	−0.752	0.198	1
New Haven–Meriden CT PMSA	0.004	0.263	−0.870	0.194	1
New Orleans LA	0.215	0.414	−0.146	0.342	3
New York NY PMSA	0.005	0.277	−1.009	0.241	2
Newark NJ PMSA	0.042	0.259	−0.811	0.203	1
Norfolk–Va Bch–Nwprt Nws VA–NC	0.377	0.460	−0.133	0.174	1
Oakland CA PMSA	0.363	0.722	−0.197	0.409	2
Oklahoma City OK	0.450	0.627	−0.091	0.243	3
Omaha NE–IA	0.527	0.667	0.040	0.259	3
Orange County CA PMSA	0.381	0.866	−0.323	0.412	2
Orlando FL	0.811	1.089	−0.203	0.222	2
Philadelphia PA–NJ PMSA	0.146	0.280	−0.767	0.124	1
Phoenix–Mesa AZ	0.908	1.419	0.228	0.434	2
Pittsburgh PA	0.198	0.304	−0.249	0.211	2
Portland–Vancouver OR–WA PMSA	0.533	0.801	−0.468	0.217	2
Providence–Fall Riv–Warw RI–MA	0.061	0.320	−0.899	0.161	1
Raleigh–Durham–Chapel Hill NC	0.749	0.934	−0.125	0.228	3
Reno NV	0.622	0.860	0.044	0.296	2
Richmond–Petersburg VA	0.356	0.589	−0.318	0.256	2
Riverside–S Bernardino CA PMSA	0.853	1.052	0.250	0.291	1
Rochester NY	0.086	0.211	−0.493	0.198	1
Sacramento CA PMSA	0.627	0.830	−0.166	0.199	1
St Louis MO–IL	0.178	0.421	−0.251	0.359	2
Salt Lake City–Ogden UT	0.740	0.955	−0.229	0.181	1
San Antonio TX	0.647	0.838	0.190	0.302	2
San Diego CA	0.501	0.889	0.031	0.464	2
San Francisco CA PMSA	0.085	0.601	−0.838	0.354	2
San Jose CA PMSA	0.162	0.665	−1.449	0.192	1
Sarasota–Bradenton FL	0.782	0.991	−0.098	0.208	2
Scranton–Wilkes–Barre–Hazl PA	0.112	0.269	−0.375	0.261	2
Seattle–Bellevue–Evrtt WA PMSA	0.400	0.654	−0.584	0.207	1
Springfield MA	−0.022	0.298	−0.700	0.261	2
Stamford–Norwalk CT PMSA	−0.003	0.426	−0.952	0.318	2
Stockton–Lodi CA	0.536	0.655	0.015	0.241	3
Syracuse NY	0.041	0.207	−0.484	0.246	2
Tampa–St Pete–Clearwater FL	0.640	0.992	−0.130	0.320	2
Toledo OH	0.159	0.436	−0.635	0.252	2
Trenton NJ PMSA	0.214	0.462	−0.391	0.347	3
Tucson AZ	0.623	1.020	0.201	0.429	4
Tulsa OK	0.434	0.630	−0.425	0.167	1
Ventura CA	0.438	0.845	−0.038	0.481	4
Washington DC–MD–VA–WV PMSA	0.353	0.604	−0.181	0.320	3
W Palm Bch–Boca Raton FL	0.742	0.974	−0.087	0.230	1
Wichita KS	0.279	0.601	−0.234	0.381	4
Wilmington–Newark DE–MD PMSA	0.302	0.673	−0.375	0.356	2
Worcester MA–CT PMSA	0.084	0.360	−1.199	0.165	1
Youngstown–Warren OH	0.013	0.247	−0.429	0.322	2

Appendix B

Data on population, land area, education, race, and place of birth come from the US Census of Population and Housing from 1990 as reported by the USA Counties 1998 on CD-ROM. Metropolitan area observations are constructed from county-level data according to 1993 definitions, which are found at http://www.census.gov/population/www/estimates/pastmetro.html. Climate data are derived for the main city of each metropolitan area from *County and City Data Book, 2000 Edition*. Average annual precipitation is based on an average over the 1961–1990 period.

There are seven metropolitan areas in New England for which the BLS reports data at the metropolitan statistical area (MSA) or primary metropolitan statistical area (PMSA) level (Boston, Hartford, New Haven–Meriden, Providence–Fall River–Warwick, Springfield, Stamford–Norwalk, and Worcester). Because MSAs and PMSAs in New England are based on towns rather than counties, counties often have parts lying in different metro areas. Because most of the data used in the analysis are reported at the county level, we have to construct approximations of all of the non-employment variables for these seven New England metro areas. We do so by aggregating all counties with some part lying in an MSA or PMSA. In practice, of course, this procedure implies that certain counties are counted as part of more than one metro area.

Because metropolitan areas frequently cross state boundaries, and US Census regions are based on states, some metropolitan areas have parts lying in more than one region. We handle these cases by assigning them to the region in which the majority of their populations reside.

Unionization rates at the metropolitan area level are based upon state-level rates reported by Hirsch et al. (2001). These can be accessed at http://www.unionstats.com. Metropolitan-area-level union rates are calculated as weighted averages of their constituent state-level rates, where the weights are given by the fraction of each metro area's labor force located in each state.

County Business Patterns provides data covering total employment and numbers of establishments for most non-governmental industries at a 4-digit level of aggregation. Due to disclosure restrictions, employment is sometimes reported as a range: 0–19; 20–99; 100–249; 250–499; 500–999; 1000–2499; 2500–4999; 5000–9999; 10,000–24,999; 25,000–49,999; 50,000–99,999; 100,000 or more. Where this occurs, we impute the employment level by taking the midpoint of the range. The largest range was not reported for any of the county-industries in the sample. Total employment in a metropolitan area is calculated by summing the employment levels across all industries so that employment shares sum to 1.

Appendix C

This appendix provides details regarding the Bayesian estimation of the model in Eqs. (1) and (2), as well as the construction of posterior odds ratios used for model comparison. Eqs. (1) and (2) can be combined as follows:

$$y_{n,t} = \delta_{S_{n,t}} + X_n' \beta_{S_{n,t}} + v_{n,S_{n,t}} + \varepsilon_{n,t}, \tag{C.1}$$

where $n = 1, \ldots, N$, $\varepsilon_{n,t} \sim$ i.i.d. $N(0, \sigma^2_{\varepsilon,n})$, $v_{n,S_{n,t}} \sim N(0, \sigma^2_{v,S_{n,t}})$, and $S_{n,t} = \{0, 1\}$ follows a two-state Markov process with transition probabilities $\Pr[S_{n,t} = i \mid S_{n,t-1} = j] = p_{ij,n}$. The model in (C.1) is a random-effects model with regime-switching parameters. Accordingly, estimation of the model will proceed by modifying existing procedures for Bayesian estimation of random-effects models to allow for regime switching.

In developing the Bayesian estimation algorithm presented below, we make the following independence assumptions: First, we assume that the model residual, $\varepsilon_{n,t}$, is uncorrelated across cities at all leads and lags, so that $\mathrm{Cov}(\varepsilon_{n=q,t}\varepsilon_{n=r,t-w}) = 0, \forall w$ and $q \neq r$. Second, we assume that the state variable, $S_{n,t}$, is independent across cities at all leads and lags. While certainly restrictive, these assumptions are necessary for estimation feasibility. In particular, without the first assumption, inference regarding the unobserved state variable would require consideration of 2^N alternative combinations of $S_{1,t}, \ldots, S_{N,t}$. The second assumption eliminates estimation of a very large ($2^N \times 2^N$) transition probability matrix required to describe the joint evolution of $S_{1,t}, \ldots, S_{N,t}$. These assumptions will be exploited in the Bayesian estimation algorithm developed below.

Bayesian estimation requires the specification of prior density functions for the model parameters. Divide the model parameters into the following blocks, given by $\tilde{\beta} = (\delta_0, \delta_1, \beta_0, \beta_1)'$, $\sigma^2_{v,0}, \sigma^2_{v,1}$, $\tilde{\sigma}^2_{\varepsilon} = (\sigma^2_{\varepsilon,1}, \ldots, \sigma^2_{\varepsilon,N})'$, $\tilde{p}_{00} = (p_{00,1}, \ldots, p_{00,N})'$ and $\tilde{p}_{11} = (p_{11,1}, \ldots, p_{11,N})'$. We assume prior independence across all parameter blocks, as well as prior independence of the elements of $\tilde{\sigma}^2_{\varepsilon}$, $\tilde{p}_{00}$, and $\tilde{p}_{11}$. The joint prior is then given by:

$$\begin{aligned} &f(\tilde{\beta}, \sigma^2_{v,0}, \sigma^2_{v,1}, \tilde{\sigma}^2_{\varepsilon}, \tilde{p}_{00}, \tilde{p}_{11}) \\ &\quad = f(\tilde{\beta}) f(\sigma^2_{v,0}) f(\sigma^2_{v,1}) \prod_{n=1}^{N} f(\sigma^2_{\varepsilon,n}) \prod_{n=1}^{N} f(p_{00,n}) \prod_{n=1}^{N} f(p_{11,n}). \end{aligned} \tag{C.2}$$

We define $f(\tilde{\beta})$ as a multivariate Gaussian random variable, with a mean vector that has its first two elements set equal to 1 and -1 respectively, and all other elements set equal to 0, and a variance-covariance matrix set equal to a diagonal matrix with all diagonal elements set equal to 5. For each $f(\sigma^2_{\varepsilon,n})$, as well as $f(\sigma^2_{v,0})$ and $f(\sigma^2_{v,1})$, we use an improper inverted-gamma density function.[25] For each $p_{00,n}$ and $p_{11,n}$, we specify Beta prior densities, given by $\beta(9, 1)$ and $\beta(8, 2)$ respectively. These priors have means of 0.9 and 0.8 and standard deviations of 0.09 and 0.12, respectively.

Given these prior density functions, Bayesian estimation aims to characterize the joint posterior density of the model parameters. We are also interested in posterior densities for other quantities of interest, including the unobserved state variables, $\tilde{S} = (\tilde{S}_1, \tilde{S}_2, \ldots, \tilde{S}_N)$, where $\tilde{S}_n = (S_{n,1}, \ldots, S_{n,T})'$, and the random effects, $\tilde{v}_0 = (v_{1,0}, v_{2,0}, \ldots, v_{N,0})'$ and $\tilde{v}_1 = (v_{1,1}, v_{2,1}, \ldots, v_{N,1})'$. Although an analytic characterization of the joint posterior density of all objects of interest is not available, we are able to obtain samples from this posterior using the Gibbs Sampler. Briefly, the Gibbs Sampler, introduced by Geman and Geman (1984), Tanner and Wong (1987) and Gelfand and Smith (1990), is an algorithm that produces random samples from the joint density of a group of random variables by repeatedly sampling from the full set of conditional density functions. Denote the data used in estimation as Y. A full set of conditional posterior density functions for the regime-switching random-effects model is then:

$$\begin{aligned} &g(\tilde{\beta} \mid \sigma^2_{v,0}, \sigma^2_{v,1}, \tilde{\sigma}^2_{\varepsilon}, \tilde{v}_0, \tilde{v}_1, \tilde{p}_{00}, \tilde{p}_{11}, \tilde{S}, Y) \\ &\quad = g(\tilde{\beta} \mid \tilde{\sigma}^2_{\varepsilon}, \tilde{v}_0, \tilde{v}_1, \tilde{S}, Y), \end{aligned} \tag{C.3}$$

$$\begin{aligned} &g(\sigma^2_{v,0}, \sigma^2_{v,1} \mid \tilde{\beta}, \tilde{\sigma}^2_{\varepsilon}, \tilde{v}_0, \tilde{v}_1, \tilde{p}_{00}, \tilde{p}_{11}, \tilde{S}, Y) \\ &\quad = g(\sigma^2_{v,0}, \sigma^2_{v,1} \mid \tilde{v}_0, \tilde{v}_1), \end{aligned} \tag{C.4}$$

$$\begin{aligned} &g(\tilde{\sigma}^2_{\varepsilon} \mid \tilde{\beta}, \sigma^2_{v,0}, \sigma^2_{v,1}, \tilde{v}_0, \tilde{v}_1, \tilde{p}_{00}, \tilde{p}_{11}, \tilde{S}, Y) \\ &\quad = g(\tilde{\sigma}^2_{\varepsilon} \mid \tilde{\beta}, \tilde{v}_0, \tilde{v}_1, \tilde{S}, Y), \end{aligned} \tag{C.5}$$

$$\begin{aligned} &g(\tilde{v}_0, \tilde{v}_1 \mid \tilde{\beta}, \sigma^2_{v,0}, \sigma^2_{v,1}, \tilde{\sigma}^2_{\varepsilon}, \tilde{p}_{00}, \tilde{p}_{11}, \tilde{S}, Y) \\ &\quad = g(\tilde{v}_0, \tilde{v}_1 \mid \tilde{\beta}, \sigma^2_{v,0}, \sigma^2_{v,1}, \tilde{\sigma}^2_{\varepsilon}, \tilde{S}, Y), \end{aligned} \tag{C.6}$$

$$\begin{aligned} &g(\tilde{p}_{00}, \tilde{p}_{11} \mid \tilde{\beta}, \sigma^2_{v,0}, \sigma^2_{v,1}, \tilde{\sigma}^2_{\varepsilon}, \tilde{v}_0, \tilde{v}_1, \tilde{S}, Y) \\ &\quad = g(\tilde{p}_{00}, \tilde{p}_{11} \mid \tilde{S}), \end{aligned} \tag{C.7}$$

$$\begin{aligned} &\Pr(\tilde{S} \mid \tilde{\beta}, \sigma^2_{v,0}, \sigma^2_{v,1}, \tilde{\sigma}^2_{\varepsilon}, \tilde{v}_0, \tilde{v}_1, \tilde{p}_{00}, \tilde{p}_{11}, Y) \\ &\quad = \Pr(\tilde{S} \mid \tilde{\beta}, \tilde{\sigma}^2_{\varepsilon}, \tilde{v}_0, \tilde{v}_1, \tilde{p}_{00}, \tilde{p}_{11}, Y). \end{aligned} \tag{C.8}$$

In each density in (C.3)–(C.8), the second expression eliminates unnecessary conditioning information. Given Y and arbitrary initial values for the other conditioning information in (C.3), the Gibbs Sampler obtains draws of all objects of interest by sampling recursively through the set of conditional posterior densities in (C.3)–(C.8). Under mild regularity conditions (Tierney, 1994) random samples obtained in this manner will converge to draws taken from the joint posterior density of interest. In simulating the posterior density, we discard the first 2000 draws to ensure convergence. Sample statistics regarding the sampled posterior density are then based on an additional 10,000 draws.

[25] The inverted-gamma density is improper in the context of O'Hagan (1994, p. 245), in that it specifies a density with infinite moments. However, this prior yields a proper posterior density (Albert and Chib, 1993; and O'Hagan, 1994, p. 292).

By combining results from the existing literature, it is straightforward to obtain random samples from each of the densities in (C.3)–(C.8). To begin, note that, conditional on $\tilde{S}$, the model in (C.1) is simply a random-effects model (with dummy variables), and the conditional posterior densities in (C.3)–(C.6) define a Gibbs Sampler for this model. For the choice of priors given above, analytic characterizations of these conditional densities are readily available (e.g., Koop, 2003, pp. 153–154).

To complete the Gibbs Sampler, we require random samples of $\tilde{p}_{11}, \tilde{p}_{00}$, and $\tilde{S}$ from (C.7)–(C.8). Given the assumptions of independence of both $\varepsilon_{n,t}$ and $S_{n,t}$ across cities, these densities reduce as follows:

$$g(\tilde{p}_{00}, \tilde{p}_{11} \mid \tilde{S}) = \prod_{n=1}^{N} g(p_{00,n}, p_{11,n} \mid \tilde{S}_n), \tag{C.9}$$

$$\Pr(\tilde{S} \mid \tilde{\beta}, \tilde{\sigma}^2_{\varepsilon}, \tilde{v}_0, \tilde{v}_1, \tilde{p}_{00}, \tilde{p}_{11}, Y) = \prod_{n=1}^{N} \Pr(\tilde{S}_n \mid \tilde{\beta}, \sigma^2_{\varepsilon,n}, v_{0,n}, v_{1,n} p_{00,n}, p_{11,n}, y_{n,1}, \ldots, y_{n,T}). \tag{C.10}$$

The elements in the products on the right-hand side of (C.9) and (C.10) are posterior densities for $p_{00,n}, p_{11,n}$, and $\tilde{S}_n$ from the Markov-switching in the mean model in Eq. (1), and can be evaluated using only employment data for city n. A draw of $\tilde{p}_{11}, \tilde{p}_{00}$, and $\tilde{S}$ from (C.7)–(C.8) is then obtained by drawing $p_{00,n}, p_{11,n}$, and $\tilde{S}_n, n = 1, \ldots, N$, using each city's employment data in isolation. For the functional forms of the priors given above, an algorithm for obtaining draws of $p_{00,n}, p_{11,n}$ and $\tilde{S}_n$ was first given in Albert and Chib (1993). For draws of $\tilde{S}_n$, we use an alternative, efficient algorithm developed by Kim and Nelson (1998) that is based on the notion of "multi-move" Gibbs Sampling introduced in Carter and Kohn (1994). Analytic characterizations for (C.9)–(C.10) are given in Kim and Nelson (1999b, pp. 212–215).

We are also interested in conducting model comparisons using the posterior odds ratio in (4). Using Bayes Rule, the posterior odds ratio can be written as:

$$P_{UR} = \frac{\Pr(M_U|Y)}{\Pr(M_R|Y)} = \frac{\Pr(M_U)}{\Pr(M_R)} \frac{f(Y|M_U)}{f(Y|M_R)}. \tag{C.11}$$

The first term on the right-hand side of (C.9) is the prior odds ratio. We give equal prior probability to each model considered, so that the prior odds ratio is unity for all model comparisons conducted. The second term is the ratio of marginal likelihoods for the unrestricted and restricted models, and is typically referred to as the Bayes Factor. To calculate the Bayes Factor we use an approach based on the Savage–Dickey Density Ratio, which is appropriate for nested model comparisons. The Savage–Dickey Density Ratio is straightforward to implement, and is described in detail in Koop (2003, pp. 69–71).

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