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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, along with the frequency of the low phase. We find that growth in the high phase is related to human capital, industry mix, and average firm size. In contrast, we find that growth in the low phase is mostly related to industry mix, specifically, the relative importance of manufacturing. Finally, the frequency of the low phase appears to be related to the level of non-education human capital, but to none of the other variables. Overall, our results strongly reject the notion that city-level characteristics influence employment growth equally across the phases of the business cycle.

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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 U.S. is located within urban areas, the growth of cities is also potentially important from the perspective of understanding aggregate U.S. economic performance.

Whereas most studies 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, Piger, and Wall (2005).

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To date, the Markov-switching approach has not been applied to city-level data, nor has it been used for serious analyses of the determinants of growth. The approach is potentially useful, however, for understanding city-level growth because the mechanisms that drive growth during a high phase may be very different from those driving growth during a low phase. For example, by reducing the likelihood of large movements in employment, industrial diversity might be more important for sustaining (or increasing) economic growth within a metropolitan area during bad times than in good times. Similarly, if the employment dynamics of small firms are more volatile over the business cycle than those of large firms, cities with a large presence of small firms may experience stronger high phases, but also weaker low 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, Scheinkman, and Shleifer, 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 than 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 larger plants are associated with faster growth during high phases, but show no association with growth in low phases, and 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: We describe our data set in Section 2 and the Markov-switching model in Section 3. Section 4 describes our estimates of high-phase and low-phase growth rates. In Section 5 we outline the specification of our growth equation, and Section 6 presents the results of our growth regression using average growth rates, estimated high-phase growth rates, and estimated low-phase growth rates. We describe the regression results for the estimated low-phase frequency in Section 7. Section 8 concludes.

2. Data

Our data are from the Current Employment Statistics (or 'payroll') survey of the Bureau of Labor Statistics. These data report quarterly estimates of total non-farm employment for all metropolitan areas in the country.[1] Because measures of employment can be extremely volatile among small cities, we restrict the sample to those with at least 200,000 in total employment as of the end of the sample time frame. Doing so produces a sample of 116 metropolitan areas. From this sample, we eliminate two metropolitan areas, 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; Kim and Nelson, 1999). Further, as found by Owyang,

[1] 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.

Piger, and Wall (2006), 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 the Appendix, 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 some measure of economic activity, y_t, be described as follows:

$$y_t = \mu_{S_t} + \varepsilon_t,$$
$$\varepsilon_t \sim N(0, \sigma_\varepsilon^2), \tag{1}$$
$$\mu_{S_t} = \mu_0 + \mu_1 S_t,\ \mu_1 < 0;$$

where the growth rate of economic activity has mean μ_{S_t}, and deviations from this mean growth rate are created by the stochastic disturbance ε_t. To capture the two phases, the mean growth rate in (1) is permitted to switch between two phases, where the switching is governed by a latent state variable, $S_t = \{0,1\}$.

When S_t switches from 0 to 1, the growth rate of economic activity switches from μ_0 to $\mu_0 + \mu_1$. Since $\mu_1 < 0$, S_t switches from 0 to 1 at times when economic activity switches from high-growth to low-growth states, or vice versa.[2] Because S_t is unobserved, estimation of (1) requires restrictions on the probability process governing S_t; in this case, we assume that S_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 last period. Under this assumption, the probability process driving S_t is captured by the transition probabilities $\Pr[S_t = j \mid S_{t-1} = i] = p_{ij}$.[3]

4. Markov-Switching Results

We estimate (1) using the multi-move Gibbs-sampling procedure implemented by Kim and Nelson (1998) for Bayesian estimation of Markov-switching models.[4] Briefly,

[2] 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.
[3] 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.
[4] See Casella and George (1992) and Kim and Nelson (1999) for detailed descriptions.

the Gibbs sampler draws iteratively from the conditional posterior distribution of each parameter (including the S_t, for $t = 1,...,T$) given the data and the draws of the other parameters of the model. These draws form an ergodic Markov chain whose distribution converges to the joint posterior distribution of the parameters given the data. In simulating this posterior distribution, we discard the first 2,000 draws to ensure convergence. Descriptive statistics regarding the sample posterior distributions are then based on an additional 10,000 draws.[5] Our point estimates are the means of these posterior distributions.

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 by Figure 1, which also shows the high-phase and low-phase growth rates as estimated by the Markov-switching model.

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

[5] Bayesian estimation requires that we specify prior distributions for the model parameters. The prior for the switching mean parameters, $[\mu_0, \mu_1]'$, is Gaussian with mean vector $[1,-1]'$ and a variance-covariance matrix equal to the identity matrix. The transition-probability parameters, p_{00} and p_{11}, have Beta prior distributions, given by $\beta(9,1)$ and $\beta(8,2)$ respectively. These priors would imply means of 0.9 and 0.8 and standard deviations of 0.09 and 0.12, respectively. The variance parameter, σ_ε^2, has an improper inverted-Gamma distribution. This prior distribution is improper in the context of O'Hagan (1994, p. 245) in that it specifies a distribution with infinite moments. However, this prior yields a proper posterior distribution (Albert and Chib, 1993; and O'Hagan, 1994, p. 292).

growth during high phases and suffered deep low phases.[6] 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 not as robust as 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 in both phases than Cleveland, 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 results of this estimation for the six cities are provided by Figure 2. For reference, the panels include shaded areas to indicate periods of national recession as

[6] Note that our results are not driven by single-quarter spikes in employment growth such as the one for New York following the Sept. 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 equation (1).

determined by the 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 1990-91 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 1990-91 and a long one in 2000-02. 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 1990-91 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 1995-96.

4.2. Results for All Cities

A few summary statistics describing the growth rates within each of the two phases, along with overall average rates of growth, appear in Table 2. From them, we can see that while low phases are indeed periods of slower employment growth than are high phases—the average low-phase growth rate is -0.38 percent per quarter and the average high-phase growth rate is 0.63 percent—there is a fair amount of variation within the sample. Low-phase growth rates range from -2.36 percent to 0.39 percent; high-phase rates extend from 0.07 percent to 1.76 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 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.[7] Metropolitan areas located in the South and the West, not surprisingly, tend to have had the highest rates of growth across both phases. Las Vegas, for instance, had the highest high-phase growth rate, 1.76 percent per quarter, while Knoxville, TN, had the highest low-phase growth rate, 0.39 percent per quarter. 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 the South and the West (e.g., San Francisco, Sarasota-Bradenton, San Jose) had relatively poor performance during their low phases.[8]

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 growth rates across the 114 cities in the sample: 0.46. There is also some overlap with overall rates of growth. The correlation between low-phase growth rates and overall average growth is 0.61; the correlation between high-phase growth rates and overall

[7] The estimated phase growth rates for all cities are in the second and third columns of numbers in a table in the Appendix.

[8] The average low-phase growth rates by region are: Northeast, -0.66; Midwest, -0.4; South, -0.29; West, -0.23. The average high-phase growth rates by region are: Northeast, 0.37; Midwest, 0.49; South, 0.74; West, 0.87.

average growth is 0.88. This result is also apparent from Table 3: Many of the fastest (slowest) growers overall are also among the fastest (slowest) growers in each phase.

5. Growth Regressions—Specification

Our intent is to determine the extent to which a set of variables commonly considered to be determinants of growth are associated with our two phase growth rates. To do so, we follow a conventional approach. For each growth rate we estimate a series of regressions in which the growth rate of city c, μ_c, is expressed as

$$\mu_c = \delta + \beta' X_c + \varepsilon_c, \tag{2}$$

where δ is a constant, X_c is a vector of city-specific characteristics, and ε_c is a residual. Among the covariates we consider in X_c are some of the most commonly used in existing studies.[9]

The variables in X_c 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

[9] 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 the Appendix.

precipitation).[10] Because the dependent variable, μ_c, is a rate of growth for the period 1990-2002, we take 1990 values of the covariates to avoid endogeneity.[11]

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. 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.[12] 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

[10] We construct metropolitan area characteristics from county-level observations using geographic definitions from 1993.
[11] Using 1980 values of the covariates did not significantly change our findings.
[12] We include finance, insurance, and real estate (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.

using the following 'Dixit-Stiglitz' index, based upon 4-digit employment data from County Business Patterns:

$$Diversity_c = \left(\sum_{i=1}^{I} \left(\frac{Emp_{ic}}{Emp_c} \right)^{0.5} \right)^2 ,$$

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

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, Kolko, and Saiz, 2001).[13]

6. Growth Regressions—Results

Before applying the empirical model to the phase growth rates, we apply it to overall average employment growth. Measures of this type, of course, form the basis of the extant literature on the determinants (or, at least, correlates) of economic growth in cities. After establishing these baseline results, we use the same empirical model for analyzing separately the high-phase and low-phase growth rates. Based on the correlation between high-phase and low-phase growth rates reported previously, 0.46, there is some indication that growth may be very different across the two phases.

[13] Although regional indicators should pick up some of the variation in climate across metropolitan areas throughout the U.S. (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.

Although this association is certainly positive and significant, it is far from perfect. Hence, there may be different characteristics of cities driving growth during each phase. To explore this possibility, we estimate a growth equation separately for the high-phase and low-phase growth rates.

6.1. Average Growth Rates

Results for the average growth rates appear in Table 4, the first column of which reports estimates from our most general specification of equation (2), which includes all of the regressors described above. On the whole, they demonstrate a number of patterns that have already been well documented. The college fraction, for example, produces a significantly positive coefficient suggesting that higher levels of human capital tend to be associated with faster rates of employment growth. The fraction of a metropolitan area's resident population that is non-white generates a significantly 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.

From the estimated region and climate coefficients, we see that metropolitan areas in the Northeast region grew substantially more slowly than those in the rest of the U.S., and that cities with higher average July temperatures grew faster than those with cooler climates. Although they are not significant, the coefficients also suggest that cities with warmer January temperatures and less precipitation exhibited faster growth, and that metropolitan areas in the South and West grew faster than those in either the Midwest or the Northeast.[14] All of 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 the share of FIRE in total employment, suggesting that, although this sector may have helped underlie the success of some cities in the U.S. (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

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

Glaeser et al. (1992), who find that industries in cities with diverse economies and relatively small firms grow faster.[15]

In an attempt to gauge the robustness of these findings, the remaining columns in Table 4 report the results from a number of different specifications in which groups of 'related' regressors have been dropped. For example, the second column drops the two scale variables, whereas the third drops the two education variables. This exercise also helps to provide a sense of the overall significance of certain types of characteristics (e.g., scale or education) rather than each individual variable. *F*-statistics from formal tests of significance of the variables that are dropped from the general model appear in the final row of the table.

In the six reported alternative specifications, we drop the following sets of variables: density and population; high school and college completion fractions; non-white and foreign-born percentages; industry shares; labor market characteristics; regional effects and climate. Based on the reported *F*-statistics, three of these groups are jointly significant: the non-white and foreign-born percentages; the three industry shares; and regional effects and climate. Education, interestingly, is not significant at conventional levels (the *p*-value is 0.11), although this result likely stems from the insignificance of the high school fraction.

As for the robustness of the estimated coefficients from the general specification, the same basic conclusions can be drawn from nearly all of the alternative specifications. To be sure, there are instances in which some of the coefficients change sign and either lose or gain statistical significance (e.g., the final specification, *VII*, which drops the

[15] 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.

region and climate variables), but these tend to be confined to specifications that drop variables that are jointly significant. We are, therefore, somewhat skeptical of the results from these alternative regressions.

6.2. High-Phase Growth Rates

Our results for the high-phase growth rates are in Table 5. Looking first at the estimates from the general model reported in the first column, many of the results look similar to those derived from the average growth rates. The college fraction and average July temperature both enter positively and significantly, while the non-white fraction and manufacturing share each produce significantly negative coefficients. Hence, cities with greater supplies of skills, warmer climates, and smaller shares of manufacturing in total employment experienced stronger high-phase growth between 1990 and 2002.[16]

There are, however, some notable differences between these findings and those for the average growth rates in Table 4. To begin, although we still find evidence that average growth and high-phase growth tended to be faster in the South and the West than in the Northeast and the Midwest, we find that employment expanded significantly faster during high phases in the West than in other parts of the country. Across the majority of the specifications, we see a significantly positive coefficient on the West region dummy.[17] Recall from Table 4 that we did not see a significant West region effect in

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[16] Interestingly, even though we have argued that the business cycle is more accurately characterized as having high and low phases, our empirical model does not fit high-phase growth rates as well as it fits average growth rates. For all seven versions of the model, the R^2s in Table 5 are lower than the corresponding ones in Table 4. Perhaps this is unsurprising given that the list of variables has been derived from a literature that has tried to explain overall average growth rates.

average rates of growth. On the other hand, recall that metropolitan areas in the Northeast exhibited significantly slower average growth. Yet, we find only limited evidence that that they grew at significantly slower rates during high phases. All but one of the coefficients for the Northeast region are insignificant.

A second difference with the average growth results concerns the role of average establishment size. 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, which, of course, offers only limited evidence against the hypothesis that small firms generate faster employment growth. From Table 5, however, we see stronger evidence against this hypothesis: there is a significantly *positive* association between average establishment size and growth during high phases. Cities organized around larger employers tend to grow faster during high phases than do those with smaller firms. Based on the magnitude of the estimated coefficient, the association is quite large. On average, doubling the average number of employees per establishment tends to be accompanied by a 0.45 percentage point increase in a city's quarterly rate of employment growth in the high phase.

The results in the remainder of Table 5 mostly reinforce the conclusions from model *I*. Many of the coefficients that are significant in the general model, *I*, tend to be significant in the alternative specifications as well. As for the joint significance of certain variables, we again find that the non-white and foreign-born variables, the three industry composition variables, and the region indicators and climate characteristics are jointly

[17] The result may also help to explain why we see significantly positive coefficients on both average temperature variables. High phases may have been particularly strong in warm climates, such as the West, leading to a strong association with temperature.

significant, just as they were with the average growth results. In addition, we now see that the two education measures (high school share and college share) are significant. Given that these two variables were not jointly significant in the average growth regressions, this result suggests that education may be more important in high phases than it is for overall growth. Finally, although average plant size is individually significant in several of the specifications, the three labor market variables as a group are jointly insignificant (the *p*-value is 0.12).

Overall, the results indicate a significant difference between the coefficients estimated in the average growth regressions and those estimated using the high-phase growth rates. A Wald test of the equivalence of the coefficients in our longest specification, *I*, across Tables 4 and 5 soundly rejects the null that the two sets of parameters are the same: the test statistic (*p*-value) is 5.88 (0).

6.3. Low-Phase Growth Rates

Turning to the low-phase growth rate results in Table 6, we see a very different set of significant coefficients than we found for the high-phase growth rate. Most notably, neither the college fraction nor the non-white percentage of the population is significant. This conclusion follows from both the individual coefficients as well as the joint tests reported at the bottom of columns *III* and *IV*. 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.[18] 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 high-phase growth is the manufacturing share of total employment. All of the estimated coefficients for this quantity are individually significant and roughly of the same magnitude. In particular, they suggest that a 10-percentage-point rise in manufacturing's share of total employment corresponds to between a 0.3- and 0.4-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 third as high. The same 10 percentage point increase in the manufacturing share is associated with a 0.1- to 0.13-percentage-point decline in the average rate of growth in the high phase. Therefore, manufacturing's well-established drag on employment growth is much stronger during low phases than during high phases.

The region indicators and climate variables offer only limited explanatory power. Individually, only annual precipitation produces a significant association, and as a group, we cannot reject the hypothesis that all six variables enter negligibly. Nevertheless, the point estimates from the region dummies may provide some interesting insights into geographic patterns of low-phase growth. Recall that high-phase growth in the West was significantly higher than in the remainder of the country, even though average growth was not. The reason for this discrepancy very likely involves growth during low phases. Although it is not significant, the West region indicator produces a negative coefficient,

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

suggesting that low phases might have been somewhat worse in western metropolitan areas than in the South. As a consequence, overall average growth was not significantly different in this region, conditional on all of the regressors considered.

Similarly, we see an insignificant association between low-phase growth and average plant size, which helps to explain why the correlation between average growth and average plant size was insignificant despite the significantly positive association with high-phase growth. Interestingly, the point estimate is mostly positive across all of the specifications, suggesting that small firms may indeed experience greater rates of job loss during low phases than do large firms. On the other hand, we also find that small firms are associated with lower rates of job increases during high phases.

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.

These results, too, are significantly different from those established above, both for average growth and high-phase growth. Wald tests reject the equivalence of the coefficients in Tables 4 and 6 and those in Tables 5 and 6.[19] Growth correlates, therefore, are sensitive to the phase of the business cycle.

[19] The *F*-statistic (*p*-value) from the test of the equivalence of the average growth and low-phase growth parameters is 2.09 (0.01). For high-phase growth and low-phase growth, it is 2.3 (0).

7. Low-Phase Frequency

Recall that overall performance, as measured by the average growth rate, is the average of the two phase growth rates weighted by the frequency of the low phase. Thus, in a Markov-switching environment, it is just as important to understand the determinants of the frequency of the phases as it is to understand those of the growth rates. To this end, this section considers what types of characteristics are associated with low-phase frequency during the sample period. Recall that estimation of the Markov-switching model provides for each period the posterior probability that a city is in a low phase. The frequency of the low phase is simply the mean of the low-phase probability across the sample period. Summary statistics appear in the bottom row of Table 2. On average, the metropolitan areas in the sample spent approximately 28 percent of the time in a low phase, which accords well with the generally expansionary nature of the time frame.[20] Yet, as indicated by the standard deviation of 0.11, there is tremendous variation within the sample. One metropolitan area, Kalamazoo-Battle Creek, MI, spent only 8 percent of the time in its low phase, whereas another, Trenton, NJ, was in its low phase nearly 75 percent of the time.

More information about the top and bottom of the distribution of low-phase frequencies can be gathered from Table 7, which reports the cities with the 10 highest and lowest frequencies.[21] 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 Sarasota-Bradenton, FL) spent relatively little time in the low phase, whereas some slow growers (e.g., Honolulu, HI) spent a large fraction of time

[20] In contrast, according to the NBER, the national economy was in recession 13.5 percent of the time.
[21] The low-phase frequencies for all cities are in the last column in a table in the Appendix.

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, 44 percent and 70 percent). On the other hand, some slow growers, including Philadelphia, PA, and Worcester, MA-CT, spent relatively little time in their low phase (respectively, 11 percent and 15 percent).[22] Overall, the correlation between average growth and low-phase frequency is only 0.06 and does not differ statistically from zero.

What types of characteristics are associated with time spent in a low-growth phase? Table 8 reports results from regressions of low-phase frequencies on the same variables considered in the growth regressions. What they show, overwhelmingly, is a general lack of significant correlations. Other than average January temperature, the only consistently significant regressor is the non-white fraction, which tends to scale positively with low-phase frequency. Again, if we interpret this variable in terms of human capital, this result suggests that less-skilled cities are in low phases more frequently. Intuitively, of course, this result is quite reasonable because less-skilled workers tend to experience worse labor market outcomes than more-skilled workers. At the same time, neither of our two education measures produces significant coefficients (although each one is negative), so the importance of human capital in explaining low-phase frequencies is not altogether straightforward.

[22] We should note that for some 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.

Very few of the remaining regressors listed in the table show any association with time spent in the low phase. This lack of significance is particularly interesting for two regressors: industrial diversity and the manufacturing share. One might expect manufacturing-based cities to have spent greater amounts of time in a low phase than in a high phase, especially given the decline of manufacturing employment in the U.S. in the past two decades. In addition, greater industrial heterogeneity should be associated with less time spent in a low phase because diverse economies ought to be less influenced by shocks to specific sectors. Yet, while manufacturing-oriented cities tend to exhibit slower rates of employment growth over time, particularly during their low phases, they do not spend more time in those low phases. Similarly, cities with diverse economies show no tendency to spend less time in a low phase than do cities with specialized economies.

The latter result, we should point out, is not necessarily inconsistent with the risk diversification hypothesis. Depending on what industries are present, some specialized economies may spend long periods of time in a low phase while others experience extremely short low phases. That is, some cities might be concentrated in growing sectors whereas others may have primarily declining sectors. Metropolitan areas with diverse economies, by contrast, might lie somewhere between these two in terms of the time they spend in a low phase. This pattern might very well generate little association between the frequency of low phases and economic diversity.

8. 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 factors separately for the average growth rate, the high-phase growth rate, the low-phase growth rate, and the low-phase frequency; and found very different sets of statistically significant variables across the four dependent variables.

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 or the frequency of low phases. 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.[23] Specifically, we found that growth in the high phase is related to several of the usual variables—human capital, industry mix, and average firm size—but that low-phase growth is related only to the relative importance of manufacturing. Finally, the low-phase frequency appears to be related to the level of non-education human capital, but to none of the other variables.

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

Appendix

Data on population, land area, education, race, and place of birth come from the U.S. 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 definitions from 1993. These definitions are given at <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 1961-90 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 U.S. 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, Macpherson, and Vroman (2001). These can be accessed at <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; 1,000-2,499; 2,500-4,999; 5,000-9,999; 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.

Average and Phase Growth Rates and Low-Phase Frequencies for all 114 Cities

	Average Growth Rate	Low-Phase Growth Rate	High-Phase Growth Rate	Low-Phase Frequency
Akron, OH PMSA	0.266	-0.204	0.474	0.333
Albany-Schenectady-Troy, NY	0.158	-0.325	0.432	0.359
Albuquerque, NM	0.603	0.323	1.280	0.700
Allentown-Bethlehem-Easton, PA	0.251	-0.101	0.568	0.450
Ann Arbor, MI PMSA	0.341	-0.526	0.485	0.222
Appleton-Oshkosh-Neenah, WI	0.503	-0.085	0.622	0.183
Atlanta, GA	0.693	-0.035	1.092	0.351
Augusta-Aiken, GA-SC	0.198	-0.139	0.377	0.401
Austin-San Marcos, TX	1.051	-0.484	1.338	0.158
Bakersfield, CA	0.430	-0.280	0.714	0.314
Baltimore, MD PMSA	0.152	-0.676	0.326	0.198
Baton Rouge, LA	0.526	-0.201	0.718	0.214
Bergen-Passaic, NJ PMSA	-0.014	-0.961	0.247	0.218
Birmingham, AL	0.372	-0.164	0.540	0.246
Boise City, ID	1.069	-0.017	1.277	0.165
Boston, MA-NH PMSA	0.094	-0.970	0.515	0.286
Buffalo-Niagara Falls, NY	0.018	-0.726	0.154	0.164
Charleston-North Charleston, SC	0.522	0.109	1.108	0.556
Charlotte-Gastonia-Rk Hill, NC-SC	0.559	-0.269	0.936	0.314
Chattanooga, TN-GA	0.317	-0.161	0.621	0.399
Chicago, IL PMSA	0.212	-0.395	0.431	0.267
Cincinnati, OH-KY-IN PMSA	0.284	-0.344	0.467	0.234
Cleveland-Lorain-Elyria, OH PMSA	0.073	-0.716	0.324	0.244
Columbia, SC	0.486	-0.739	0.799	0.217
Columbus, OH	0.453	-0.279	0.659	0.222
Dallas, TX PMSA	0.613	-0.411	0.964	0.256
Dayton-Springfield, OH	0.034	-0.575	0.245	0.271
Denver, CO PMSA	0.616	-0.536	0.831	0.157
Des Moines, IA	0.433	0.005	0.626	0.338
Detroit, MI PMSA	0.170	-0.618	0.479	0.281
El Paso, TX	0.429	-0.262	0.542	0.180
Fort Wayne, IN	0.229	-0.582	0.485	0.245
Fort Worth-Arlington, TX PMSA	0.565	-0.235	0.873	0.278
Fresno, CA	0.564	0.207	0.688	0.338
Ft Lauderdale, FL PMSA	0.641	-0.142	0.838	0.217
Gary, IN PMSA	0.133	-0.308	0.244	0.279
Gr Rapids-Muskegon-Holland, MI	0.503	-0.371	0.821	0.266
Grnsboro-Winston-Salem-Hi Pt, NC	0.304	-0.761	0.521	0.184
Grnville-Spartanb-Anderson, SC	0.314	-1.028	0.562	0.161
Harrisburg-Lebanon-Carlisle, PA	0.307	0.049	0.377	0.260
Hartford, CT	-0.160	-0.868	0.066	0.217
Honolulu, HI	0.068	-0.180	0.575	0.603
Houston, TX PMSA	0.590	0.168	0.940	0.479
Indianapolis, IN	0.426	-0.041	0.610	0.286
Jackson, MS	0.425	0.068	0.668	0.396
Jacksonville, FL	0.537	-0.127	0.863	0.330
Jersey City, NJ PMSA	0.001	-1.102	0.432	0.276
Johnson City-Kingsp-Bris, TN-VA	0.312	0.011	0.524	0.425
Kalamazoo-Battle Creek, MI	0.155	-1.943	0.324	0.075
Kansas City, MO-KS	0.375	-0.422	0.611	0.235
Knoxville, TN	0.563	0.386	0.883	0.554
LA-Long Beach, CA PMSA	-0.050	-0.627	0.364	0.378
Lancaster, PA	0.321	-0.003	0.512	0.367
Lansing-East Lansing, MI	0.222	-0.175	0.303	0.257
Las Vegas, NV-AZ	1.375	0.327	1.764	0.296

Lexington, KY	0.423	-0.756	0.605	0.152
Little Rock-N Little Rock, AR	0.467	-0.050	0.610	0.265
Louisville, KY-IN	0.360	-0.548	0.614	0.218
Madison, WI	0.623	0.259	0.719	0.305
Mdlesex-Somerset-Hunterd, NJ PMSA	0.323	-0.549	0.626	0.259
Memphis, TN-AR-MS	0.384	-0.069	0.675	0.393
Miami, FL PMSA	0.269	-0.490	0.537	0.260
Milwaukee-Waukesha, WI PMSA	0.219	-0.458	0.399	0.216
Minneapolis-St Paul, MN-WI	0.428	-0.245	0.613	0.220
Mobile, AL	0.506	-0.326	0.698	0.198
Monmouth-Ocean, NJ PMSA	0.364	-0.605	0.569	0.173
Nashville, TN	0.592	-0.187	0.858	0.263
Nassau-Suffolk, NY PMSA	0.149	-0.757	0.367	0.200
New Haven-Meriden, CT PMSA	0.004	-1.046	0.208	0.168
New Orleans, LA	0.215	-0.148	0.334	0.300
New York, NY PMSA	0.005	-0.928	0.335	0.264
Newark, NJ PMSA	0.042	-0.812	0.259	0.211
Norfolk-Va Bch-Nwprt Nws, VA-NC	0.377	-0.095	0.446	0.233
Oakland, CA PMSA	0.363	-0.166	0.742	0.417
Oklahoma City, OK	0.450	-0.156	0.601	0.219
Omaha, NE-IA	0.527	0.048	0.671	0.300
Orange County, CA PMSA	0.381	-0.293	0.863	0.416
Orlando, FL	0.811	-0.356	1.095	0.200
Philadelphia, PA-NJ PMSA	0.146	-0.857	0.271	0.115
Phoenix-Mesa, AZ	0.908	0.239	1.435	0.439
Pittsburgh, PA	0.198	-0.281	0.315	0.205
Portland-Vancouver, OR-WA PMSA	0.533	-0.440	0.816	0.238
Providence-Fall Riv-Warw, RI-MA	0.061	-0.907	0.324	0.162
Raleigh-Durham-Chapel Hill, NC	0.749	0.071	1.026	0.299
Reno, NV	0.622	-0.093	0.872	0.266
Richmond-Petersburg, VA	0.356	-0.334	0.588	0.254
Riverside-S Bernardino, CA PMSA	0.853	0.282	1.114	0.336
Rochester, NY	0.086	-0.407	0.219	0.229
Sacramento, CA PMSA	0.627	-0.279	0.795	0.160
Salt Lake City-Ogden, UT	0.740	-0.257	0.944	0.183
San Antonio, TX	0.647	0.212	0.843	0.312
San Diego, CA	0.501	0.066	0.910	0.479
San Francisco, CA PMSA	0.085	-0.989	0.516	0.291
San Jose, CA PMSA	0.162	-2.362	0.576	0.138
Sarasota-Bradenton, FL	0.782	-2.127	0.967	0.087
Scranton-Wilkes-Barre-Hazl, PA	0.112	-0.385	0.282	0.282
Seattle-Bellevue-Evrtt, WA PMSA	0.400	-0.588	0.643	0.267
Springfield, MA	-0.022	-0.721	0.289	0.254
St Louis, MO-IL	0.178	-0.235	0.408	0.358
Stamford-Norwalk, CT PMSA	-0.003	-0.945	0.432	0.308
Stockton-Lodi, CA	0.536	0.225	0.659	0.326
Syracuse, NY	0.041	-0.770	0.149	0.172
Tampa-St Pete-Clearwater, FL	0.640	-0.143	1.003	0.318
Toledo, OH	0.159	-0.738	0.436	0.238
Trenton, NJ PMSA	0.214	-0.008	0.977	0.736
Tucson, AZ	0.623	0.088	0.821	0.309
Tulsa, OK	0.434	-0.696	0.582	0.122
Ventura, CA	0.438	0.004	0.913	0.510
W Palm Bch-Boca Raton, FL	0.742	-0.045	0.989	0.247
Washington, DC-MD-VA-WV PMSA	0.353	-0.166	0.565	0.300
Wichita, KS	0.279	-0.353	0.509	0.328
Wilmington-Newark, DE-MD PMSA	0.302	-0.397	0.690	0.356
Worcester, MA-CT PMSA	0.084	-1.498	0.367	0.152
Youngstown-Warren, OH	0.013	-0.602	0.235	0.298

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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.

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
Low-Phase Growth Rate	-0.38	0.47	-2.36	0.39
High-Phase Growth Rate	0.63	0.3	0.07	1.76
Fraction of Time in Low Phase	0.28	0.11	0.08	0.74

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

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	1.76	Knoxville, TN	0.39
Phoenix-Mesa, AZ	1.44	Las Vegas, NV-AZ	0.33
Austin-San Marcos, TX	1.34	Albuquerque, NM	0.32
Albuquerque, NM	1.28	Riverside-San Bernardino, CA	0.28
Boise City, ID	1.28	Madison, WI	0.26
Riverside-San Bernardino, CA	1.11	Phoenix-Mesa, AZ	0.24
Charleston-North Charleston, SC	1.11	Stockton-Lodi, CA	0.22
Orlando, FL	1.10	San Antonio, TX	0.21
Atlanta, GA	1.09	Fresno, CA	0.21
Raleigh-Durham-Chapel Hill, NC	1.03	Houston, TX	0.17
Lowest		**Lowest**	
Newark, NJ	0.26	Bergen-Passaic, NJ	-0.96
Bergen-Passaic, NJ	0.25	Boston, MA-NH	-0.97
Dayton-Springfield, OH	0.24	San Francisco, CA	-0.99
Gary, IN	0.24	Greenville-Spartanburg-Anderson, SC	-1.03
Youngstown-Warren, OH	0.23	New Haven-Meriden, CT	-1.05
Rochester, NY	0.22	Jersey City, NJ	-1.10
New Haven-Meriden, CT	0.21	Worcester, MA-CT	-1.50
Buffalo-Niagara Falls, NY	0.15	Kalamazoo-Battle Creek, MI	-1.94
Syracuse, NY	0.15	Sarasota-Bradenton, FL	-2.13
Hartford, CT	0.07	San Jose, CA	-2.36

Note: Growth rates represent quarterly percentage changes.

Table 4. Regression Results—Average Growth Rates

	I	II	III	IV	V	VI	VII
Log Density	-0.025 (0.03)	--	-0.02 (0.03)	-0.08* (0.03)	-0.025 (0.03)	-0.027 (0.027)	-0.08* (0.03)
Log Population	0.006 (0.04)	--	0.02 (0.04)	0.003 (0.05)	0.017 (0.04)	0.005 (0.03)	0.09* (0.04)
% High School	0.045 (0.72)	-0.15 (0.7)	--	1.82* (0.68)	0.68 (0.67)	0.29 (0.72)	-1.5* (0.65)
% College	0.99* (0.59)	0.84 (0.53)	--	1.67* (0.62)	1.35* (0.5)	1.14* (0.52)	-0.16 (0.53)
% Non-white	-1.2* (0.2)	-1.3* (0.2)	-1.17* (0.18)	--	-0.98* (0.2)	-1.1* (0.17)	-1.02* (0.19)
% Foreign-born	-0.24 (0.36)	-0.37 (0.31)	-0.21 (0.31)	--	-0.31 (0.34)	-0.29 (0.35)	-0.13 (0.35)
% Manufacturing	-1.6* (0.52)	-1.6* (0.5)	-1.45* (0.52)	-0.9* (0.5)	--	-1.28* (0.45)	-2.49* (0.56)
% Services	-0.83 (0.61)	-0.85 (0.58)	-0.52 (0.63)	-0.35 (0.73)	--	-0.63 (0.69)	-1.25* (0.67)
% FIRE	-1.24 (1.1)	-1.35 (1.1)	-0.43 (1.06)	-0.56 (1.02)	--	-0.95 (0.97)	-1.98* (1.18)
% Union Coverage	-0.1 (0.39)	-0.12 (0.39)	-0.32 (0.4)	-0.54 (0.56)	0.02 (0.43)	--	-1.12* (0.31)
Industrial Diversity	-0.0002 (0.0006)	-0.0003 (0.0003)	-0.0005 (0.0005)	0.0006 (0.0006)	-0.0002 (0.0006)	--	-0.001* (0.0005)
Log Avg. Plant Size	0.22 (0.19)	0.23 (0.19)	0.23 (0.18)	-0.14 (0.22)	-0.11 (0.19)	--	0.33 (0.23)
Avg. January Temp.	0.003 (0.003)	0.003 (0.003)	0.002 (0.002)	-0.001 (0.003)	0.002 (0.003)	0.002 (0.003)	--
Avg. July Temp.	0.02* (0.004)	0.02* (0.004)	0.015* (0.004)	0.014* (0.005)	0.023* (0.006)	0.019* (0.004)	--
Annual Precipitation	-0.002 (0.002)	-0.002 (0.002)	-0.001 (0.002)	-0.004* (0.002)	-0.002 (0.002)	-0.002 (0.002)	--
Northeast Region	-0.23* (0.09)	-0.21* (0.09)	-0.22* (0.07)	-0.27* (0.09)	-0.29* (0.09)	-0.26* (0.07)	--
Midwest Region	-0.09 (0.07)	-0.08 (0.07)	-0.09 (0.06)	-0.12 (0.08)	-0.13 (0.08)	-0.1 (0.07)	--
West Region	0.09 (0.1)	0.12 (0.1)	0.13 (0.1)	0.02 (0.12)	0.13 (0.11)	0.08 (0.09)	--
R^2	0.75	0.75	0.73	0.66	0.71	0.75	0.65
F-stat. for omitted variables (*p*-value)	--	0.47 (0.62)	2.25 (0.11)	19.85 (0.00)	5.19 (0.00)	0.54 (0.66)	6.88 (0.00)

Note: 114 observations; heteroskedasticity-consistent standard errors are reported in parentheses. An asterisk (*) denotes significance at 10 percent or better.

Table 5. Regression Results—High-Phase Growth Rates

	I	II	III	IV	V	VI	VII
Log Density	0.006 (0.04)	--	0.02 (0.04)	-0.05 (0.04)	0.003 (0.04)	0.002 (0.04)	-0.08* (0.04)
Log Population	-0.05 (0.07)	--	-0.024 (0.06)	-0.05 (0.07)	-0.03 (0.06)	-0.02 (0.05)	0.06 (0.07)
% High School	-0.2 (0.93)	-0.2 (0.85)	--	1.53* (0.8)	0.39 (0.85)	0.2 (0.9)	-1.57* (0.8)
% College	1.32* (0.69)	1.25* (0.6)	--	1.99* (0.7)	1.66* (0.56)	1.58* (0.61)	0.35 (0.63)
% Non-white	-1.14* (0.25)	-1.16* (0.24)	-1.04* (0.23)	--	-0.94* (0.26)	-0.99* (0.2)	-0.8* (0.28)
% Foreign-born	-0.28 (0.43)	-0.29 (0.41)	-0.17 (0.39)	--	-0.36 (0.41)	-0.41 (0.43)	0.33 (0.5)
% Manufacturing	-1.33* (0.67)	-1.34* (0.67)	-1.08 (0.72)	-0.68 (0.66)	--	-0.67 (0.62)	-2.36* (0.67)
% Services	-0.41 (0.9)	-0.57 (0.84)	0.04 (0.97)	0.03 (0.98)	--	-0.12 (1.02)	-0.83 (1)
% FIRE	-1.32 (1.3)	-1.27 (1.26)	-0.11 (1.2)	-0.69 (1.2)	--	-0.61 (1.1)	-2.3* (1.3)
% Union Coverage	-0.52 (0.54)	-0.55 (0.53)	-0.84 (0.54)	-0.93 (0.6)	-0.39 (0.57)	--	-1.34* (0.4)
Industrial Diversity	0.0001 (0.0008)	-0.0004 (0.0005)	-0.0003 (0.0006)	0.0009 (0.0008)	-0.00004 (0.0008)	--	-0.0009 (0.0007)
Log Avg. Plant Size	0.45* (0.24)	0.44* (0.24)	0.45* (0.22)	0.11 (0.24)	0.16 (0.24)	--	0.43 (0.27)
Avg. January Temp.	0.008* (0.003)	0.007* (0.003)	0.006* (0.003)	0.004 (0.003)	0.007* (0.003)	0.006* (0.003)	--
Avg. July Temp.	0.02* (0.006)	0.018* (0.005)	0.015* (0.006)	0.015* (0.006)	0.023* (0.007)	0.02* (0.006)	--
Annual Precipitation	-0.001 (0.003)	-0.001 (0.003)	-0.0005 (0.003)	-0.003 (0.003)	-0.001 (0.003)	-0.002 (0.002)	--
Northeast Region	-0.09 (0.12)	-0.09 (0.12)	-0.1 (0.09)	-0.15 (0.11)	-0.15 (0.12)	-0.2* (0.1)	--
Midwest Region	-0.005 (0.1)	-0.01 (0.09)	-0.03 (0.08)	-0.04 (0.09)	-0.05 (0.1)	-0.08 (0.09)	--
West Region	0.24* (0.14)	0.25* (0.13)	0.29* (0.13)	0.17 (0.14)	0.27* (0.13)	0.2 (0.12)	--
R^2	0.67	0.67	0.64	0.61	0.64	0.65	0.54
F-stat. for omitted variables (*p*-value)	--	0.28 (0.75)	3.84 (0.02)	11.6 (0.00)	2.5 (0.06)	2.03 (0.12)	7.44 (0.00)

Note: 114 observations; heteroskedasticity-consistent standard errors are reported in parentheses. An asterisk (*) denotes significance at 10 percent or better.

Table 6. Regression Results—Low-Phase Growth Rates

	I	II	III	IV	V	VI	VII
Log Density	-0.09 (0.07)	--	-0.09 (0.07)	-0.1 (0.06)	-0.08 (0.06)	-0.09 (0.07)	-0.12* (0.06)
Log Population	-0.016 (0.12)	--	-0.03 (0.12)	-0.01 (0.12)	-0.008 (0.1)	0.03 (0.09)	0.05 (0.1)
% High School	0.86 (1.8)	0.12 (1.9)	--	1.3 (1.8)	2.4 (1.9)	1.1 (1.8)	-0.76 (1.5)
% College	-0.21 (1.2)	-0.85 (1.3)	--	-0.009 (1.2)	0.78 (1.1)	-0.1 (1.3)	-1.23 (1.11)
% Non-white	0.26 (0.6)	-0.06 (0.5)	0.14 (0.6)	--	0.81 (0.66)	0.39 (0.64)	-0.09 (0.41)
% Foreign-born	-0.79 (0.69)	-1.26 (0.86)	-1.01 (0.7)	--	-0.9 (0.72)	-0.92 (0.66)	-0.76 (0.67)
% Manufacturing	-3.88* (1.5)	-3.94* (1.5)	-4.07* (1.6)	-4.12* (1.6)	--	-3.24* (1.52)	-4.22* (1.31)
% Services	-2.46 (1.7)	-2.65* (1.6)	-2.67 (1.7)	-2.6 (1.8)	--	-2.26 (1.6)	-2.46* (1.49)
% FIRE	-1.75 (2.1)	-2.11 (2.07)	-2.33 (2.02)	-2.19 (2.02)	--	-0.99 (1.8)	-2.04 (2.2)
% Union Coverage	-0.3 (1.04)	-0.42 (0.99)	-0.16 (1)	-0.26 (0.99)	-0.04 (1.05)	--	-0.16 (0.72)
Industrial Diversity	0.0007 (0.002)	-0.0004 (0.001)	0.0007 (0.002)	0.0006 (0.002)	0.0008 (0.002)	--	-0.0005 (0.002)
Log Avg. Plant Size	0.43 (0.53)	0.45 (0.54)	0.48 (0.51)	0.55 (0.56)	-0.38 (0.67)	--	0.77 (0.51)
Avg. January Temp.	-0.0004 (0.008)	0.0005 (0.008)	0.001 (0.008)	-0.003 (0.006)	-0.002 (0.008)	-0.002 (0.009)	--
Avg. July Temp.	0.006 (0.01)	0.008 (0.009)	0.007 (0.01)	0.008 (0.01)	0.02* (0.01)	0.008 (0.008)	--
Annual Precipitation	-0.01* (0.004)	-0.01* (0.005)	-0.01* (0.004)	-0.009* (0.004)	-0.01* (0.05)	-0.01* (0.004)	--
Northeast Region	-0.12 (0.21)	-0.05 (0.21)	-0.07 (0.19)	-0.2 (0.21)	-0.29 (0.21)	-0.18 (0.18)	--
Midwest Region	-0.04 (0.17)	-0.004 (0.16)	0.01 (0.16)	-0.09 (0.16)	-0.14 (0.17)	-0.09 (0.18)	--
West Region	-0.18 (0.19)	-0.08 (0.17)	-0.19 (0.19)	-0.16 (0.19)	-0.08 (0.18)	-0.19 (0.16)	--
R^2	0.35	0.34	0.34	0.34	0.27	0.34	0.31
F-stat. for omitted variables (*p*-value)	--	1.15 (0.32)	0.33 (0.72)	0.79 (0.46)	2.64 (0.05)	0.46 (0.71)	1.38 (0.23)

Note: 114 observations; heteroskedasticity-consistent standard errors are reported in parentheses. An asterisk (*) denotes significance at 10 percent or better.

Table 7. Highest and Lowest Low-Phase Frequencies

City	Fraction of Time in Low Phase
Highest	
Trenton, NJ	0.74
Albuquerque, NM	0.70
Honolulu, HI	0.60
Charleston-North Charleston, SC	0.56
Knoxville, TN	0.55
Ventura, CA	0.51
San Diego, CA	0.48
Houston, TX	0.48
Allentown-Bethlehem-Easton, PA	0.45
Phoenix-Mesa, AZ	0.44
Lowest	
Sacramento, CA	0.16
Austin-San Marcos, TX	0.16
Denver, CO	0.16
Lexington, KY	0.15
Worcester, MA-CT	0.15
San Jose, CA	0.14
Tulsa, OK	0.12
Philadelphia, PA	0.11
Sarasota-Bradenton, FL	0.09
Kalamazoo-Battle Creek, MI	0.08

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

Table 8. Regression Results—Low-Phase Frequencies

	I	II	III	IV	V	VI	VII
Log Density	0.006 (0.02)	--	0.005 (0.02)	0.01 (0.02)	0.005 (0.02)	0.004 (0.02)	-0.015 (0.016)
Log Population	-0.04 (0.04)	--	-0.04 (0.03)	-0.04 (0.04)	-0.03 (0.03)	-0.03 (0.03)	-0.024 (0.036)
% High School	-0.1 (0.58)	-0.1 (0.56)	--	-0.29 (0.46)	-0.03 (0.6)	0.04 (0.5)	0.03 (0.4)
% College	-0.02 (0.31)	-0.08 (0.32)	--	-0.08 (0.28)	0.036 (0.3)	0.08 (0.33)	0.11 (0.3)
% Non-white	0.34* (0.17)	0.32* (0.16)	0.35* (0.14)	--	0.35* (0.17)	0.39* (0.13)	0.37* (0.15)
% Foreign-born	-0.25 (0.2)	-0.26 (0.18)	-0.23 (0.17)	--	-0.26 (0.2)	-0.3 (0.2)	0.1 (0.16)
% Manufacturing	-0.09 (0.36)	-0.1 (0.36)	-0.07 (0.38)	-0.32 (0.38)	--	0.15 (0.37)	-0.11 (0.32)
% Services	0.1 (0.48)	-0.03 (0.4)	0.11 (0.5)	-0.04 (0.5)	--	0.21 (0.48)	0.12 (0.5)
% FIRE	-0.15 (0.6)	-0.1 (0.6)	-0.12 (0.6)	-0.46 (0.59)	--	0.09 (0.6)	-0.28 (0.58)
% Union Coverage	-0.2 (0.35)	-0.23 (0.34)	-0.2 (0.34)	-0.1 (0.3)	-0.17 (0.35)	--	0.09 (0.17)
Industrial Diversity	0.00002 (0.0004)	-0.0004 (0.0003)	0.00003 (0.0004)	-0.0002 (0.0004)	-0.00005 (0.0004)	--	0.00002 (0.0003)
Log Avg. Plant Size	0.16 (0.13)	0.15 (0.13)	0.15 (0.12)	0.27* (0.13)	0.14 (0.14)	--	0.1 (0.1)
Avg. January Temp.	0.004* (0.002)	0.003 (0.002)	0.004* (0.002)	0.003* (0.002)	0.004* (0.002)	0.003 (0.002)	--
Avg. July Temp.	-0.002 (0.003)	-0.003 (0.003)	-0.002 (0.003)	-0.0005 (0.003)	-0.002 (0.003)	-0.001 (0.003)	--
Annual Precipitation	-0.001 (0.002)	-0.0008 (0.002)	-0.001 (0.001)	-0.00003 (0.002)	-0.001 (0.001)	-0.001 (0.001)	--
Northeast Region	0.1 (0.06)	0.11* (0.06)	0.09 (0.06)	0.08 (0.06)	0.1 (0.07)	0.06 (0.06)	--
Midwest Region	0.07 (0.05)	0.065 (0.05)	0.07 (0.05)	0.07 (0.08)	0.07 (0.05)	0.046 (0.5)	--
West Region	0.05 (0.07)	0.5 (0.07)	0.05 (0.07)	0.07 (0.08)	0.05 (0.07)	0.03 (0.06)	--
R^2	0.22	0.2	0.22	0.17	0.21	0.2	0.16
F-stat. for omitted variables (*p*-value)	--	0.78 (0.46)	0.2 (0.98)	3.06 (0.05)	0.13 (0.94)	1.04 (0.38)	1.41 (0.22)

Note: 114 observations; heteroskedasticity-consistent standard errors are reported in parentheses. An asterisk (*) denotes significance at 10 percent or better.

Figure 1. Employment Growth Rates for Selected Cities
Thick black (gray) line is estimated high-phase (low-phase) growth rate.

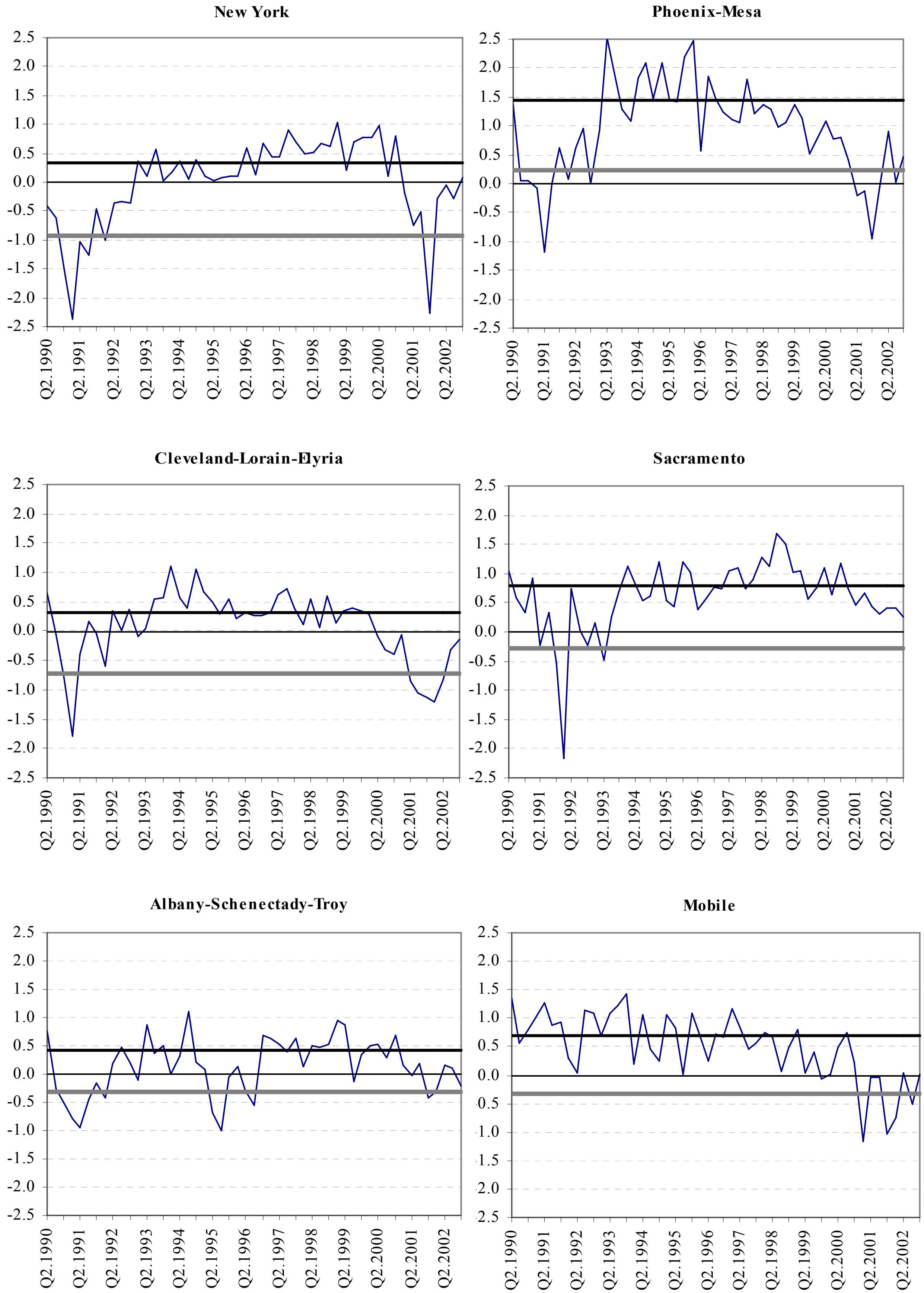

Figure 2. Low-Phase Probabilities for Selected Cities
Gray shaded areas indicate national NBER recessions.