# A Statistical Test of City Growth: Location, Increasing Returns and Random Growth

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**Abstract**

This article analyzes the main existing theories on income and population city growth: the existence of increasing returns to scale, the importance of locational fundamentals, and random growth. To do this we develop a nonlinearity test that is implemented to a dataset on urban, climatological and macroeconomic variables on 1,175 U.S. cities. The conclusions of our analysis are that there are increasing returns to scale on city income growth; nevertheless, the most important variables to explain income growth are locational fundamentals. Both sets of variables need to be jointly considered to avoid inconsistent model parameter estimates. We also observe increasing returns to scale on population growth; larger cities grow at a faster pace than smaller cities. These cities are not, however, within the group of wealthiest cities implying the existence of a threshold on population beyond which per-capita income growth stagnates or even deteriorates.

**Key words**: threshold nonlinearity test, locational fundamentals, multiple equilibria, random growth

**JEL Classification**: C12, C13, C33, O1, R0, R11

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# 1 Introduction

There are differences in the growth rates of cities. It is evident that some cities (or regions) are more productive than others, or attract more population, and several explanations have been proposed to try to explain these differentiated behaviors. Following Davis and Weinstein (2002), these theoretical explanations can be grouped into three main theories: the existence of increasing returns to scale, the importance of locational fundamentals, and the absence of both (random growth).

The first theory is supported by theoretical models of the New Economic Geography. These models often obtain nonlinear behaviours and multiple equilibria as a consequence of their basic assumptions, very different from the classic framework: mobile factors, the existence of transport costs and centrifugal and centripetal forces (centripetal forces favour the agglomeration of activity, such as increasing returns, whereas centrifugal forces favour dispersion, such as congestion costs), the presence of Marshallian external economies, the importance of expectations and of the small initial advantages, which can eventually produce a global advantage (economics of qwerty), etc. Literature on urban increasing returns, also known as agglomeration economies, is wide (see the meta-analysis by Melo et al., 2009). The traditional sources of external economies of scale are labor market pooling, input sharing, and knowledge spillovers (Marshall, 1920). Recently, Duranton and Puga (2004) provide an alternative perspective; agglomeration economies could be driven by sharing, matching or learning mechanisms. In addition, there is also evidence that other factors contribute to agglomeration: home market effects, consumption opportunities, and rent-seeking (see the survey by Rosenthal and Strange, 2004). The role of sorting and selection has also been emphasized (Combes et al., 2008; Combes et al., 2009).

Locational fundamentals are exogenous factors linked to the physical landscape, such as temperature, rainfall, access to the sea, the presence of natural resources or the availability of arable land. These characteristics are randomly distributed across space and, although they may have played a crucial role in early settlements, one would expect that their influence decreases over time. However, empirical studies demonstrate that their important influence in determining agglomeration still remains. For the case of the United States, Ellison and Glaeser (1999) state that natural advantages, such as the presence of a natural harbour or a particular climate, can explain about 20 percent of the observed geographic concentration. Glaeser and Shapiro (2003) find that in the 1990s people moved to warmer, dryer places. Black and Henderson (1998) conclude that the extent of city growth and mobility are related to natural advantages or geography. Beeson et al. (2001) show that access to transport networks, either natural (oceans) or produced (railroads) was an important source of growth during the period 1840-1990, and that climate is one of the factors promoting population growth. And Mitchener and McLean (2003) find that some geographical characteristics account for a high proportion of the differences in productivity levels between American states.

Random growth theories are based on stochastic growth processes and probabilistic models. The most important models are Champernowne (1953), Simon (1955), and more recently, Gabaix (1999) or Córdoba (2008). In the case of population growth these models are able to reproduce two empirical regularities well-known in urban economics: Zipf's and Gibrat's laws (or the rank-size rule and the law of proportionate growth). Both are considered to be two sides of the same coin. While Gibrat's Law has to do with the population growth process, Zipf's Law refers to its resulting population distribution.

There are many studies on each of the different theories. However, literature considering the alternative approaches at the same time is shorter; only Davis and Weinstein (2002, 2008) and Bloom, Canning and Sevilla (2003) adopt such a broad perspective. The first authors support a hybrid theory in which locational fundamentals establish the spatial pattern of relative regional densities, but increasing returns help to determine the degree of spatial differentiation in Japanese cities. Similarly, Bloom, Canning and Sevilla (2003) study the influence of climatological and geographical variables on growth, at a country level. These authors develop a Markov regime-switching model to analyze whether locational fundamentals have additional explanatory power to describe per-capita income growth compared to nonlinear models based on lagged per-capita income. Finally, Davis and Weinstein (2008) develop a threshold regression framework for distinguishing the hypothesis of unique versus multiple equilibria, and apply it to the Allied bombing of Japan during World War II finding evidence against multiple equilibria. Bosker et al. (2007) replicate this analysis for the bombing of Germany during World War II and their results support a model with two stable equilibria.

Our work contributes to this literature by developing a formal nonlinearity test robust to the presence of locational variables that we apply to urban, climatological and macroeconomic data from U.S. cities in the 1990s. This nonlinear model allows us to test for the presence of multiple growth regimes, which is one of the core topics in urban and regional economics, and one of the advantages of our procedure is that we can identify the threshold value. Our results provide evidence of increasing returns to scale on both per-capita income and population growth. At the same time, we observe that the more explicative variables are those that correspond to socioeconomic and environmental variables, what we call locational fundamentals. One of the main conclusions of our model is that the largest U.S. cities have increasing returns to scale on population growth but are not in the group of cities with highest per-capita income. One explanation for this is that despite the concentration of human capital, technology and strong financial and public administration sectors, these cities also have higher inflation rates, more taxes and expensive housing. Also, these cities suffer from a large heterogeneity in the characteristics of their inhabitants due to more intense immigration inflows, concentration of ethnic minorities, or creation of ghettos, with difficult access to the labour market causing per-capita income to drop. In equilibrium, these individuals should flee to less densely populated cities and more employment opportunities. Instead, we observe that the dynamics of population growth are more persistent than those of per-income growth, leading us to think that these large cities can become poverty traps for these disadvantaged groups.

The rest of the article is structured as follows. Section 2 sets out the econometric framework and discusses the different hypothesis tests of interest. Section 3 discusses the empirical results for a database containing 1,175 U.S. cities and Section 4 concludes. The algorithm with the econometric nonlinearity test is found in the Appendix.

## 2 Econometric Methodology

An equation similar to the national income identity for an open economy is used to measure city income. The structural factors contributing to city income are consumption, investment, trade, and local government expenditures, among others. All these variables depend in turn on a set of socioeconomic and geographical variables, denominated city characteristics and locational fundamentals hereafter, that determine the economic size of a city. These variables include literacy variables as schooling, socioeconomic variables as productive structure or unemployment rate, and geographical and environmental variables such as temperature, climate or access to the sea. Our interest is then in studying the influence of these explanatory variables in the aggregate measure of city per-capita income. This variable is obtained from modeling separately city income growth and population growth. For both aggregate response variables we have two working hypotheses defined by a linear and a nonlinear model on a cross-sectional two-period model.

Let $y_{io}$ and $l_{io}$ denote log initial income and log initial population for city $i$, $y_{if}$ and $l_{if}$ are the corresponding terminal period variables and $x_{io}$ is a vector of socio-economic and geographical indicators. The linear model for income growth is

$$\Delta y_i = \beta_0 + \beta_1 y_{io} + \beta_2' x_{io} + \varepsilon_i, \tag{1}$$

with $\Delta y_i = y_{if} - y_{io}$, $\beta_0$ the intercept of the model, $(\beta_1, \beta_2')$ a vector of parameters describing the marginal effect of the regressors, and $\varepsilon_i$ is an independent and identically distributed ($iid$) error term with constant variance.

The study of population growth follows similarly. Let $L_{io}$ be the initial level of population and $L_{if}$ terminal period population levels; the structural equation to describe population in city $i$ is

$$L_{if} = births_{if} - deaths_{if} + \text{net immigration flows}_{if} + L_{io}.$$

Since the interest is in analyzing the aggregate dynamics of population growth in terms of $x_{io}$ we concentrate, instead, on the regression equation

$$\Delta l_i = \eta_0 + \eta_1 l_{io} + \eta_2' x_{io} + \varepsilon_i^*, \tag{2}$$

with $\Delta l_i = l_{if} - l_{io}$ and $\varepsilon_i^*$ a mean zero $iid$ error term with constant variance, that can be correlated to $\varepsilon_i$ for some $i$; $\eta_0$, $\eta_1$ and $\eta_2$ are the parameters describing the marginal effect of the explanatory variables. Economic foundations for equation (2) can be found in the theoretical framework of urban growth put forward in Glaeser et al. (1995), and further explicated in Glaeser (2000). This is a model of spatial equilibrium similar to the Roback (1982) model, where the relationship between population growth and initial characteristics is determined by changes in the demand for some aspect of the city's initial endowment in production or consumption, or by the effect of this initial characteristic on productivity growth.

Putting together expressions (1) and (2) we can obtain the regression equation for per-capita income. This is given by

$$\Delta \dot{y}_i = \gamma_0 + \gamma_1 \dot{y}_{io} + \gamma_2 l_{io} + \gamma_3' x_{io} + v_i, \tag{3}$$

with $\dot{y}_i = y_i - l_i$ denoting per-capita income, $\gamma_0 = \beta_0 - \eta_0$, $\gamma_1 = \beta_1$, $\gamma_2 = \beta_1 - \eta_1$, $\gamma_3 = \beta_2 - \eta_2$ and $v_i = \varepsilon_i - \varepsilon_i^*$ a mean zero error term with variance equal to the sum of each error variance contribution minus twice the covariance term. This is the well-known expression of the conditional $\beta$-convergence (Evans, 1997; Evans and Karras, 1996a; 1996b). There are several theoretical economic growth models that can produce equation (3) at the state-, county-, or region- level. For a neoclassical growth model, see Barro and Sala-i-

Martin (1992). The nonlinear alternative to (3) is motivated by the interest in macroeconomics and the empirical growth literature in determining the existence of unique or multiple equilibria in per-capita income growth[1]. Thus, theoretical papers on the existence of convergence clubs or conditional convergence are, for example, Baumol (1986), De Long (1988) or Quah (1993, 1996, 1997). In our framework, the nonlinear alternative, assuming the presence of at most two regimes in per-capita income, is

$$\Delta \dot{y}_i = \gamma_0 + \gamma_{11}\dot{y}_{io}I(\dot{y}_{io} \leq u) + \gamma_{12}\dot{y}_{io}I(\dot{y}_{io} > u) + \gamma_2 l_{io} + \gamma_3' x_{io} + w_i, \tag{4}$$

with $I(\cdot)$ an indicator variable taking the value of one when the argument is true and zero otherwise; and $w_i$ a new $iid$ mean zero error term[2]. For $\gamma_{11} < \gamma_{12}$, the model describes the existence of increasing returns to scale for values of initial per-capita income greater than a threshold value $u$ defined on a compact space $U \in \mathbb{R}$.

This cross-sectional regression equation allows us to test via likelihood ratio methods different hypotheses of interest in empirical city growth models. This is detailed in the following section. This model extends the study of Durlauf and Johnson (1995) by providing a formal procedure for dividing the sample. Equations (3) and (4) can be estimated by ordinary least squares methods as long as the error term is uncorrelated to $\dot{y}_o$ and the $x_o$ vector. It is worth mentioning that if there is no threshold effect this methodology causes a lack of efficiency in parameter estimation due to an artificial split of the available sample. Likewise, if the threshold effect is known to happen in some specific variable of the set $x_o$ one can alternatively devise nonlinear methods that only affect that variable and allow to use the full sample to estimate the relation between the response variable and the rest of explanatory variables. Statistically, this produces more efficient estimators, on the other hand, there is the inconvenience of having more convoluted models. This micro-treatment

[1]We consider the possibility of only one or two different growth regimes, as the maximum number of multiple equilibria found in previous works is two (Bosker et al., 2007). A similar study can be easily carried out for more than two regimes. The qualitative gains obtained from including more regimes are outweighted by the increase in computational complexity.

[2]Alternatively, the nonlinear model (4) can be obtained from considering a threshold nonlinearity in either model (2), (3) or both. For simplicity we choose to describe the nonlinearity in the per-capita income model rather than in the aggregate variables $y_i$ and $l_i$.

of the model is beyond the scope of this paper.

## 2.1 Estimation of the different models

Before discussing the test statistics and asymptotic theory we note that the estimation of the above models can be done via ordinary least squares (OLS). Let $z_i(u) = [1 \ \dot{y}_{io} I(\dot{y}_{io} \leq u) \ \dot{y}_{io} I(\dot{y}_{io} > u) \ l_{io} \ x_{io} \ ]$ for any given $u$, and $\gamma(u)$ be a vector with the coefficients of the nonlinear model (4). For a sample of $N$ observations, $Z(u)$ and $\Delta Y$ denote the corresponding matrix and vector of observations. Model parameters are estimated by

$$\widehat{\gamma}(u) = \left(Z(u)'Z(u)\right)^{-1} Z(u)'\Delta Y.$$

The vector of residuals from the cross-sectional regression is $e(u) = \Delta Y - Z(u)\widehat{\gamma}(u)$. Following Chan (1993) and Hansen (1997) the estimation of the threshold parameter is done by minimization of the concentrated sum of squared residuals of each model: $\widehat{S}(u) = e(u)'e(u)$. Hence the least squares estimator of $u$ is

$$\widehat{u} = \arg\min_{u \in U} \widehat{S}(u), \tag{5}$$

with $U$ a compact set in the positive domain of the real line. The residual variance of the nonlinear model is $\widehat{\sigma}^2(u) = \frac{1}{N-1}\widehat{S}(u)$. Under the null linear hypothesis the residual variance is $\widehat{\sigma}^2_o = \frac{1}{N-1}\sum_{n=1}^{N} e^2_{o,i}$, with $e_{o,i} = \Delta y_i - \widehat{\gamma}_0 - \widehat{\gamma}_1 y_{i0} - \widehat{\gamma}_2 l_{io} - \widehat{\gamma}_3' x_{io}$ obtained from model (3) by OLS methods.

## 2.2 Testing the three leading theories

The above models permit to derive hypothesis tests for each of the leading hypotheses in the analysis of cross-sectional city growth: increasing returns, random growth and locational fundamentals. We use the methods developed in Hansen (1997) to test for the existence of multiple equilibria in cross-sectional growth models. The nonlinear model (4) allows us to test for the different hypotheses using simple likelihood ratio (LR) tests. Similarly, we analyze the existence of increasing returns to scale in population growth and the statistical validity of Gibrat's law.

### 2.2.1 Existence of Increasing Returns to Scale vs Locational Fundamentals

The first hypothesis under study is the existence of increasing returns to scale. Under increasing returns to scale accumulation of output beyond a threshold $u$ makes cities more productive[3]. In model (4) this hypothesis is the alternative of the test $H_{OI} : \gamma_{11} = \gamma_{12}$ vs $H_{AI} : \gamma_{11} \neq \gamma_{12}$. There are several methods to test the hypothesis. As Hansen (1997), we focus on $LR$ tests, also denominated F-tests in regression analysis. The choice of $u$ is endogenous to the data, hence standard econometric asymptotic theory cannot be applied, instead, we need to approximate the critical values of the test by simulation methods. To do this we define an auxiliary process indexed by the threshold $u$;

$$F(u) = N\left(\frac{\widehat{\sigma}_o^2 - \widehat{\sigma}^2(u)}{\widehat{\sigma}^2(u)}\right), \tag{6}$$

with $\widehat{\sigma}_o^2$ and $\widehat{\sigma}^2(u)$ the estimated variance of the error term under the null and alternative hypotheses, respectively. For $u$ known this process is asymptotically distributed as a $\chi^2$ with degrees of freedom equal to the number of constraints in the model. Otherwise, it converges weakly to a nonlinear function of a Gaussian process with covariance kernel that depends on moments of the sample, and thus critical values cannot be tabulated. Following Davies (1977, 1987) and Andrews and Ploberger (1994) the test statistics that we propose are the supremum, average and exponential average. Andrews and Ploberger (1994) show that the exponential average test is optimal in terms of power in very general frameworks. On the other hand, the supremum test has the advantage of providing very valuable information about the location of the rejection, and hence of the threshold value. The null

[3] This is a macroeconomic approach to increasing returns. However, some of the exogenous variables, i. e. human capital variables, are considered in the literature as source of aglomeration economics from a microeconomic perspective, see Duranton and Puga (2004). As mentioned above, the micro-treatment of the model is beyond the scope of this paper.

finite-sample distribution of these statistics is constructed using bootstrap methods. The procedure is described in an algorithm in the appendix. For the supremum, average or exponential average cases this bootstrap procedure gives a random sample $(\mathcal{T}s^{(1)}, \ldots, \mathcal{T}s^{(B)})$ of $B$ simulated observations. The empirical p-value is computed as the percentage of these artificial observations which exceed the actual test statistic, $\mathcal{T}s$:

$$\widehat{p}^B = \frac{1}{B}\sum_{b=1}^{B} I(\mathcal{T}s^{(b)} \geq \mathcal{T}s).$$

Hansen (1996) shows that this empirical p-value converges, under smooth conditions and for the null and alternative hypothesis, to the true asymptotic p-value. This hypothesis test allows us to determine the statistical significance of the nonlinearity compared to the linear model.

The second hypothesis of interest is the statistical significance of locational fundamentals. In order to be robust to the existence of per-capita income increasing returns to scale we propose the hypothesis test $H_{0L} : \gamma_3 = 0$ vs $H_{A,L} : \gamma_3 \neq 0$ in model (4). One of the few and pioneering studies concerned with the impact of locational fundamentals is Bloom, Canning and Sevilla (2003). These authors, however, are interested in modeling the presence of nonlinearities in per-capita income growth from country-level data and using a model that incorporates potential effects of climatological and geographical variables. These authors develop a Markov regime-switching model in which the probabilities that determine the change of regime depend on the locational fundamentals set of variables.

Another competing theory for explaining income growth is that of random growth, that is, no explanatory variable helps to systematically explain city growth income. The null hypothesis in model (4) is $H_{OR} : \gamma_{11} = \gamma_{12} = \gamma_2 = \gamma_3 = 0$. This hypothesis can be also explored using model (3).

### 2.2.2 Population Growth

A hypothesis test related to the latter hypothesis of random growth is Gibrat's law. Under this hypothesis population growth is random, and hence cannot be explained by past growth, or other urban or macroeconomic variables. This hypothesis can be implemented from different regression models. The simplest case considers

$$\Delta l_i = \eta_0 + \eta_1 l_{io} + \varepsilon_i^*. \tag{7}$$

More convoluted versions of the test, as model (2), also allow for possible effects of urban, climatological or macroeconomic variables. In particular, we look at the population counterpart of (4) that considers possible nonlinearities of lagged population levels under the presence of locational fundamentals. The relevant regression model is

$$\Delta l_i = \eta_0 + \eta_{11} l_{io} I(l_{io} \leq \nu) + \eta_{12} l_{io} I(l_{io} > \nu) + \eta_2 x_{io} + \varepsilon_i, \tag{8}$$

with $\nu$ the population threshold value.

In the subsequent empirical analysis, Gibrat's law is tested using regression equations (7) and (8) and the simulation methods above discussed.

# 3 Empirical Results

This section illustrates the above econometric models and tests for data from all cities in the Unites States with more than 25,000 inhabitants in the year 2000 (1,175 cities). The dataset includes urban, climatological, locational and macroeconomic variables on all these 1,175 cities.

## 3.1 Data

The data came from the census[4] for 1990 and 2000. We identified cities as what the U.S. Census Bureau calls incorporated places. Two census designated places (CDPs) are also included (Honolulu CDP in Hawaii and Arlington CDP in Virginia). The U.S. Census Bureau uses the generic term "incorporated place"to refer to a type of governmental unit incorporated under state law as a city, town (except the New England states, New York, and Wisconsin), borough (except in Alaska and New York), or village, and having legally prescribed limits, powers, and functions. On the other hand there are the unincorporated places (which were renamed Census Designated Places, CDPs, in 1980), which designate a statistical entity, defined for each decennial census according to Census Bureau guidelines, comprising a densely settled concentration of population that is not within an incorporated place, but is locally identified by a name. They are the statistical counterpart of the incorporated places. The difference between them is in most cases merely political and/or administrative. Thus for example, due to a state law of Hawaii there are no incorporated places there; they are all unincorporated.

The geographic boundaries of census places can change between censuses. As in Glaeser and Shapiro (2003), we address this issue by controlling for change in land area. Although this control may not be appropriate because it is also an endogenous variable that may reflect the growth of the city, none of our results change significantly if this control is excluded. Moreover, we also eliminated cities that either more than doubled land area or lost more than 10 percent of their land area[5]. This correction eliminates extreme cases where the city in 1990 is something very different from the city in 2000.

The explicative variables chosen are similar to those in other studies on city growth in the U.S. and city size, and correspond to the initial 1990 values. The influence of some of these variables on city size has been empirically proven by other works (Glaeser et

[4]The US Census Bureau offers information on a large number of variables for different geographical levels, available on its website: www.census.gov.

[5]Land area data also comes from US Census Bureau: http://www.census.gov/population/www/censusdata/places.html, and http://www.census.gov/geo/www/gazetteer/places2k.html.

al., 1995; Glaeser and Shapiro, 2003). Our aim is to introduce variables to control for some of the already known empirical determinants of city growth (human capital, density, or weather). Table 1 presents the variables, which can be grouped in four types: urban sprawl variables, human capital variables, productive structure variables, and geographical variables.

Urban sprawl variables are basically intended to reflect the effect of city size on urban growth. For this, we use population density (inhabitants per square mile), growth in land area from 1990-2000 (as a control for boundary changes), and the variable median travel time to work (in minutes) representing the commuting cost borne by workers. Commuting time is endogenous and depends in part on the spatial organization of cities and location choice within cities. The median commuting time may reflect traffic congestion in larger urbanized areas, but might also reflect the size of the city in less densely populated areas, or the remoteness of location for rural towns. This is one of the most characteristic costs of urban growth, explicitly considered in some theoretical models; that is, the idea that as a city's population increases, so do costs in terms of individuals' travel time to work.

Regarding human capital variables, there are many studies demonstrating the influence of human capital on city size, as cities with better educated inhabitants tend to grow more. Simon and Nardinelli (2002) analyse the period 1900–1990 for the U.S. and conclude that cities with individuals with greater levels of human capital tend to grow more, and Glaeser and Saiz (2003) analyse the period 1970–2000 and show that this is due to skilled cities being more productive economically. We took two human capital variables: Percentage population 18 years and over: High school graduate (includes equivalency) or higher degree, and Percentage population 18 years and over: Some college or higher degree. The former represents a wider concept of human capital, while the latter centres on higher educational levels (some college, Associate degree, Bachelor's degree, and Graduate or professional degree).

The third group of variables, referring to productive structure, contains the unemployment rate and the distribution of employment by sectors. The distribution of labor among the various productive activities provides valuable information about other city characteristics. Thus, the employment level in the primary sector (agriculture; forestry; fishing and hunting; and mining) also represents a proxy of the natural physical resources available to the city (cultivable land, port, etc.) This is also a sector which, like construction, is characterized by constant or even decreasing returns to scale.

Employment in manufacturing informs us of the level of local economies of scale in production, as this is a sector which normally presents increasing returns to scale. The level of pecuniary externalities also depends on the size of the industrial sector. Marshall put forward that (i) the concentration of firms of a single sector in a single place creates a joint market of qualified workers, benefiting both workers and firms (labour market pooling); (ii) an industrial centre enables a larger variety at a lower cost of concrete factors needed for the sector which are not traded (input sharing), and (iii) an industrial centre generates knowledge spillovers. This approach forms part of the basis of economic geography models, along with circular causation: workers go to cities with strong industrial sectors, and firms prefer to locate nearer larger cities with bigger markets. Thus, industrial employment also represents a measurement of the size of the local market. Another proxy for the market size of the city is the employment in commerce, whether retail or wholesale. Information is also included on employment in the most relevant activities in the services sector: Finance, insurance, and real estate, Educational, health, and other professional and related services, and employment in the Public administration.

We disaggregate "geography" into physical geography and the socio-economic environment. We try to control for both types of characteristics. We use a temperature index as a measure of weather[6]. The temperature discomfort index ($TEMP\_INDEX$) represents each city's climate amenity, and it is constructed as in Zheng et al. (2009) or Zheng et al.

[6]These data are the 30-year average values computed from the data recorded during the period 1971-2000. Source: U.S. National Oceanic and Atmospheric Administration (NOAA), National Climatic Data Center (NCDC), Climatography of the United States, Number 81 (http://cdo.ncdc.noaa.gov/cgi-bin/climatenormals/climatenormals.pl).

(2010). It is defined as:

$$TEMP\_INDEX_k = \sqrt{\begin{array}{c} (\text{Winter\_temperature}_k - \min(\text{Winter\_temperature}))^2 + \\ + (\text{Summer\_temperature}_k - \max(\text{Summer\_temperature}))^2 \end{array}}.$$

It represents the distance of the $k-$city's winter and summer temperatures from the mildest winter and summer temperatures across the 1,175 cities. A higher $TEMP\_INDEX$ means a harsher winter or a hotter summer, which makes the city a harder place where to live or to produce.

Finally, we include several dummies which give us information about geographic localization, and which take the value 1 depending on the region (Northeast Region, Midwest Region, South Region or the West Region) and the state in which the city is located. These dummies show the influence of a series of variables for which individual data are not available for all places, and which could be directly related to the geographical situation (access to the sea, presence of natural resources, etc.), or, especially, the socio-economic environment (differences in economic and productive structures).

## 3.2 Econometric analysis

The first study concerns the existence of increasing/decreasing returns to scale in per-capita income. The p-value obtained from the simulation method discussed above is zero for the average, exponential average and supremum tests applied to model (4). The supremum test also provides a threshold estimate for initial per-capita income of $\widehat{u}_n = 9.866$. The process $F(u)$ is non-monotone and shows different points in which the null hypothesis of linearity is rejected. Figure 1 shows this process and the histogram of the supremum of the $F(u)$ test under the null hypothesis.

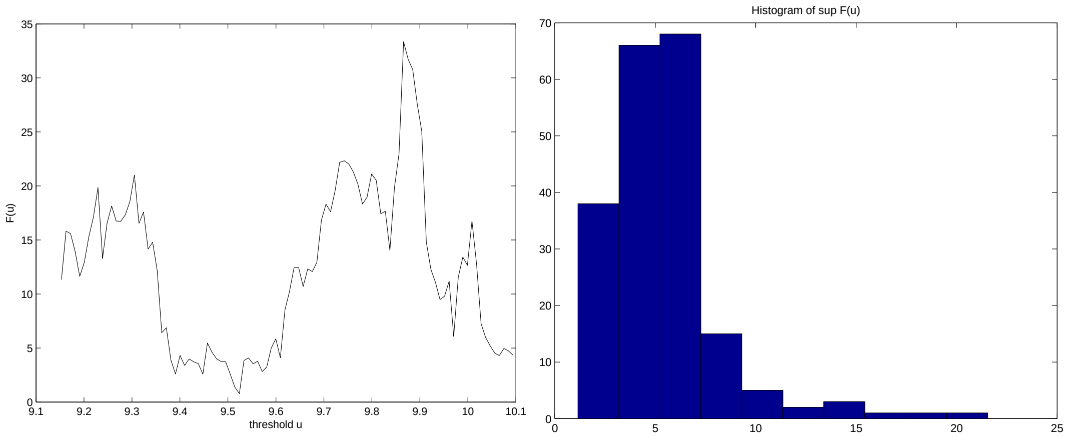


Figure 1. $F(u)$ and histogram of the supremum of $F(u)$

In model (4), the threshold estimate defines two regimes characterized by the lagged income variable: for values below 9.866 the parameter estimate is $\widehat{\gamma}_{11} = -0.1356$, and $\widehat{\gamma}_{12} = -0.1308$ for values higher than the threshold. The statistical test uncovers two distinct equilibria, and hence the existence of increasing returns to scale for cities with income levels in 1989 beyond $y_0 = 9.866$. There are 163 cities in this group[7]. Although the two values are very close, the difference is statistically significant as the nonlinearity test corroborates. The results are consistent with economic growth theory in what the sign of the parameters is negative indicating convergence towards equilibrium. Barro and Sala-i-Martin (1992), Evans and Karras (1996a, 1996b), Sala-i-Martin (1996), and Evans (1997) also find statistically significant $\beta$-convergence effects using U.S. state-level data, and Higgins et al. (2006) use U.S. county-level data to document statistically significant $\beta$-convergence effects across the United States. Nevertheless, our analysis is more informative; in particular it provides empirical evidence of nonlinear dynamics in per-capita income growth across cities. A more detailed analysis of the increasing returns to scale uncovered by the above nonlinearity test shows that it is California the state with more cities in this group. In fact, $38\%$ of the cities in this group are in this state. The average of the variables under study for all the sample and also for the group of cities beyond the threshold on per-capita income is reported in Table 4. These results show that cities in the

[7]The list of cities within this group is shown in Appendix.

wealthiest group not only share high per-capita wealth but also high education levels, high population growth and are densely populated cities. The descriptive analysis of the sectors of productive activity also reveals that these cities' main economic activity are services: financial, insurance, real estate and educational, health and other professional and related services. It is also interesting to observe that in contrast to European centres of economic activity, for the wealthiest U.S. cities the Public Administration sector is less important and contributes less to city development compared to middle and lower income cities.

The second question that we aim to answer is whether locational fundamentals and city characteristics add explanatory power to the nonlinear version of the standard growth regression equation. The p-value of the test $H_{0L} : \gamma_3 = 0$ in model (4) is zero. Locational fundamentals and initial city characteristics have a significant statistical effect for explaining per-capita income growth. The rejection of the null hypothesis also shows that locational fundamentals and city characteristics have a different marginal effect on income growth than on population growth. A similar regression analysis is carried out to test for $H'_{0L} : \gamma_{11} = \gamma_{12} = 0$ using (4) versus the alternative that lagged per-capita income helps to explain income growth. The F-test clearly shows that this variable statistically matters. The p-value is zero again. These results demonstrate that U.S. cities have increasing returns to scale on per-capita income growth in the 1990s. Nevertheless, the adjusted $R^2$ of the unreported regressions including 69 explanatory variables indicates that the main driving force explaining the response variable is locational fundamentals. Further, a closer look to the parameter estimates of the model under $H_{0L}$ and the unrestricted model (4) shows a large variation in these estimates across models. This finding points out the presence of endogeneity in the restricted regression due to the correlation between locational fundamentals in 1990 and that year's income. By including the vector $x$ in the regression equation the differences in parameter estimates vanish.

Finally, as a byproduct of this analysis we observe that dummy variables accounting for the effect of the U.S. state are not statistically significant in most cases. To add robustness to our analysis and for illustration purposes, we have repeated the whole experiment for a smaller set of locational fundamentals without the 'state' dummy variables. Table 2 reports the results of the different regression equations and F-statistics. The outcomes of the different hypothesis tests are identical to the analysis of the complete model. Results obtained in other studies are also confirmed. For example, higher levels of the wider measure of human capital (high school or higher degree) have a positive and significant effect on income growth, or the percentage of employment in manufacturing has a negative effect. Manufacturing's negative effect on income growth was previously found by Glaeser et al. (1995) for the period 1960–1990; its explanation is related to the depreciation of capital, suggesting that cities followed the fortunes of the industries that they were initially devoted to. The effect of the temperature index is also negative, indicating that a higher index means that the city is a harder place in which to produce.

The second part of the analysis on city growth concerns the study of population. We first compute the test $H_{0G} : \eta_1 = 0$ for the simple regression relating population growth and log of population in 1990. The result of the test clearly rejects Gibrat's law. The F-statistic is 104.31. Two further tests for the marginal effect of per-capita income and locational fundamentals show that the effect of both sets of variables do matter to explain population growth. The last empirical exercise is to test for the nonlinearity of the regression model (8). The p-values corresponding to the exponential average and supremum tests are zero. Figure 2 illustrates the dynamics of the $F(\nu)$ process in terms of $\nu$ and the histogram of the $supF(\nu)$ test under the null hypothesis.

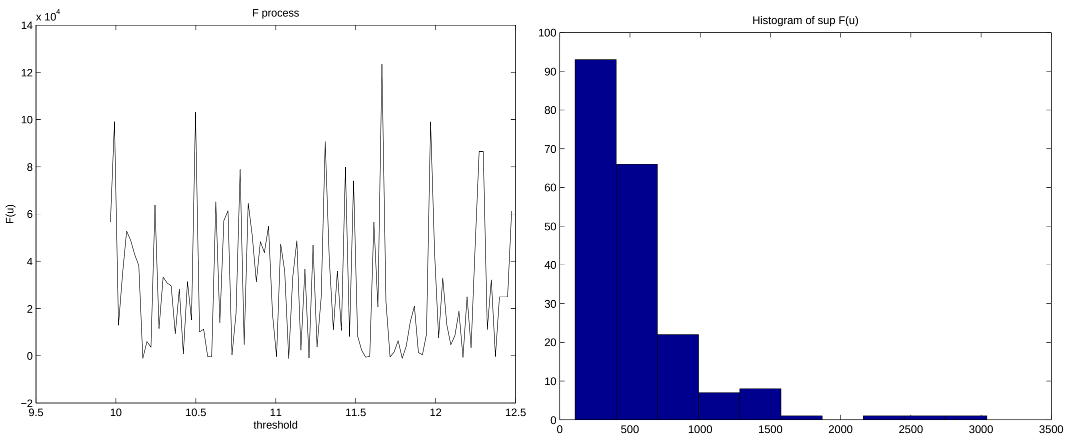

Figure 2. $F(\nu)$ and histogram of the supremum of $F(\nu)$

The threshold estimate is now $\widehat{u}_n = 11.6639$ leaving 149 observations beyond the threshold[8] and dividing the sample into two groups characterized by initial log population. The parameter estimates are $\widehat{\eta}_{21} = -0.044$ for cities with initial log population below the threshold and $\widehat{\eta}_{22} = -0.036$ for the remaining cities in the sample. The p-value of the test implies that Gibrat's law is rejected for our sample and evaluation period. Thus, we find that past population levels influence future population levels. Moreover, the estimates of the model parameters along with the statistical significance of the test make us conclude that population growth exhibits increasing returns to scale producing the existence of city clusters in terms of population size.

Table 4 also provides very interesting insights on the characteristics of the group of cities with largest population growth. Most of these cities are in the South of the U.S. and share some features with the group of wealthiest cities, for example, they seem to be largely populated cities with dense areas and growth in the land area below the total average across U.S. cities. However, in contrast to the previous case we observe that cities growing at a faster pace are also characterized by a strong Public Administration sector, high unemployment rates and low educational levels. The average per-capita income level for this group is below the average. The list in the appendix shows that cities with different idiosyncracies are mixed leading to inconclusive results. It is interesting to note that the largest U.S. cities are also those that grow faster.

As before, this analysis is repeated suppressing the effect of dummy U.S. state variables. In this case we obtain the same qualitative results. Table 3 details the specific marginal effects of the different variables. It is worth mentioning the differences in the magnitude and sign of the model parameter estimates for the different regressions. This gives a clear indication of the existence of endogeneity in the data when relevant explanatory variables are excluded from the analysis. More conclusions on the results of the empirical analysis can be obtained from Table 3. The influence of the unemployment rate is worth discussing

[8]The composition of this group is shown in Appendix.

separately. The regression estimates show that the unemployment rate has no significant effect on income growth but a clear negative influence on population growth. This means that unemployment's main effect concerns individual's movements rather than city's productivity. We also observe that cities with high unemployment experience lower population growth rates. This result is in contrast to the previous finding that noted that high population growth cities have higher than average unemployment rates. Both results combined stress the heterogeneity in living conditions observed in individuals living in these cities.

The results also show opposing behavior for the two human capital variables we introduced; increases in the percentage of population with the highest education level (some college or higher degree) have a positive impact on population growth, while the wider concept of human capital (high school graduate or higher degree) has a significant negative effect. These results coincide with those of other studies analyzing the influence of education on city growth. Glaeser and Shapiro (2003) also find workers have a different impact depending on their education level[9] (high school or college). Finally, the influence of climate on population growth is weaker. Temperature index has a negative effect on growth, as expected: a higher index means that the city is a harder place in which to live. However, this coefficient lost significance when all the variables were included.

# 4 Conclusion

The empirical analysis of city growth has been open to debate by researchers in Urban and Geographical Economics since long ago. Whereas some studies claim that city growth is nonlinear due to increasing returns to scale, other studies postulate that city growth is linear but affected by locational fundamentals, that is, the socioeconomic and geographical conditions defining a city are the key variables to characterize city growth. So far, these studies have been divided into separate analyses of population growth and per-capita income growth, and more importantly, most of these studies have been based on econometric

[9] In their sample of cities, the different effect is completely due to the impact of California.

methods based on estimation but where no formal statistical test has been implemented.

This study has proposed a battery of threshold nonlinearity tests for different intertwined hypotheses concerning the dynamics of per-capita income and population growth. The tests make use of formal statistical methods and simulation techniques to approximate the relevant asymptotic critical values, and are well suited to test for the existence of increasing returns to scale/locational fundamentals in a framework robust to the presence of locational fundamentals/increasing returns to scale. The conclusions of our empirical analysis covering a large sample comprising 1,175 U.S. cities are that there are small, although statistically significant, increasing returns to scale on city income growth. Nevertheless, the most important variables to explain income growth are locational fundamentals, and hence a proper analysis needs to account for both types of explanatory variables. For population growth we observe increasing returns to scale: larger cities grow at a faster pace than smaller cities. As for per-capita income growth, locational fundamentals have also more explanatory power than lagged population to describe population growth.

The split between cities obeying per-capita income differences is more informative than the division for population growth. The wealthiest cities are those that have highest education levels, blue collar jobs in the financial and educational sectors, and surprisingly, have a public administration sector with a smaller relative contribution to per-capita income than in the average city. These cities are also within the group of cities that grow at a faster pace and more densely populated. However, the descriptive analysis also suggests that in the group of cities with increasing returns to scale on population growth there are also cities with high unemployment rates, a large share of public administration workers and lower educational levels. A subgroup from this class of cities with increasing returns on population growth is that of the largest U.S. cities. These cities are important centres of economic and industrial activity, but at the same time, have higher inflationary pressures, more expensive housing or a larger amount of taxes. They also attract domestic and foreign immigration, unskilled workers and people with low income perspectives that bring down the average per-capita income. The creation of ghettos of low income individuals or from disadvantaged ethnic minorities is also more likely to occur in large cities than in middle and small size cities. All these factors play an important role in the large variability observed in their per-capita income levels.

Our results also show that the nonlinear dynamics in population growth are more persistent than the corresponding nonlinear income growth dynamics reinforcing the fact that as cities become larger their per-capita income stagnates or even deteriorates, as it can be the case if current income levels drop below the threshold. This empirical analysis suggests the existence of an optimal size beyond which cities lose standards of living. More work is however needed to formalize this idea.

# Appendix

## Algorithm to approximate p-value of nonlinearity test

- Generate a grid of $j = 1, \ldots, m$ different $u$ values, with $u \in U$ a compact set, let $\Gamma = (u_1, \ldots, u_m)$.

- Generate a sequence of $N$ observations $\{\varepsilon_{0,i}^{(b)}\}_{i=1}^{N}$ indexed by $b$ with $b = 1, \ldots, B$, from a $N(0,1)$ distribution.

- Regress $\varepsilon_{0,i}^{(b)}$ on the set of explanatory variables in model (3) to obtain the residuals: $e_{0,i} = \varepsilon_{0,i}^{(b)} - \widehat{\gamma}_0 - \widehat{\gamma}_1 \dot{y}_{io} - \widehat{\gamma}_2 l_{io} - \widehat{\gamma}_3' x_{io}$ with $i = 1, \ldots, N$ and compute $\widehat{\sigma}_o^{2(b)}$.

- Estimate process (4) with response variable $\{\varepsilon_{0,i}^{(b)}\}_{i=1}^{N}$, and obtain the corresponding model parameter estimates under the alternative hypothesis.

- Compute the corresponding residuals $e_i(u_j) = \varepsilon_{0,i}^{(b)} - \widehat{\gamma}_0 - \widehat{\gamma}_{11} \dot{y}_{io} I(\dot{y}_{io} \leq u) - \widehat{\gamma}_{12} \dot{y}_{io} I(\dot{y}_{io} > u) - \widehat{\gamma}_2 l_{io} - \widehat{\gamma}_3 x_{io}$, and estimated error variance $\widehat{\sigma}^{2(b)}(u_j)$.

- Set $F^{(b)}(u_j) = (N-1)\left(\frac{\widehat{\sigma}_o^{2(b)} - \widehat{\sigma}^{2(b)}(u_j)}{\widehat{\sigma}^{2(b)}(u_j)}\right)$ and $F^{(b)}(u_j) = (N-1)\left(\frac{\widehat{\sigma}_o^{2(b)} - \widehat{\sigma}^{2(b)}(u_j)}{\widehat{\sigma}^{2(b)}(u_j)}\right)$ for each $u_j \in U$ and $b = 1, \ldots, B$.

- Compute $\mathcal{T}s^{(b)} = \sup_{u \in U} F^{(b)}(u_j)$, $\mathcal{T}a^{(b)} = \underset{u \in U}{ave}\ F^{(b)}(u_j)$ and $\mathcal{T}e^{(b)} = \exp \underset{u \in U}{ave}\ F^{(b)}(u_j)$ for each $b = 1, \ldots, B$.

- Compute the empirical p-value:

$$\widehat{p}^B = \frac{1}{B} \sum_{b=1}^{B} I(\mathcal{T}^{(b)} \geq \mathcal{T}),$$

  with $\mathcal{T}^{(b)} = \mathcal{T}s^{(b)}$, or $\mathcal{T}a^{(b)}$ or $\mathcal{T}e^{(b)}$; and $\mathcal{T}$ the test statistic computed from the original available sample.

## Cities within groups

Cities with initial income levels beyond the threshold estimate ($\widehat{u}_n = 9.866$) are Alameda city, Alexandria city, Alpharetta city, Anchorage municipality, Arcadia city, Arlington CDP, Arlington Heights village, Ballwin city, Bedford city, Bellevue city, Belmont city, Benicia city, Beverly Hills city, Bloomington city, Boca Raton city, Bowie city, Brea city, Brookfield city, Buffalo Grove village, Burlingame city, Camarillo city, Cambridge city, Carlsbad city, Carmel city, Cary town, Chesterfield city, Claremont city, Coconut Creek city, Coppell city, Coral Gables city, Culver City city, Cupertino city, Dana Point city, Danbury city, Danville town, Delray Beach city, Diamond Bar city, Downers Grove village, Dublin city, Eden Prairie city, Edina city, Edmonds city, Elmhurst city, Encinitas city, Englewood city, Evanston city, Fair Lawn borough, Farmington Hills city, Fort Lauderdale city, Fort Lee borough, Foster City city, Fountain Valley city, Fremont city, Friendswood city, Germantown city, Glen Cove city, Glen Ellyn village, Glenview village, Grapevine city, Gurnee village, Hackensack city, Highland Park city, Hilton Head Island town, Hoboken city, Hoover city, Huntington Beach city, Irvine city, Juneau city and borough, Jupiter town, Keller city, Kirkland city, Kirkwood city, Laguna Niguel city, Lake Oswego city, Leawood city, Lenexa city, Livermore city, Long Beach city, Los Altos city, Los Gatos town, Madison city, Manhattan Beach city, Martinez city, Melrose city, Menlo Park city, Minnetonka city, Mission Viejo city, Morgan Hill city, Mount Prospect village, Mountain View city, Naperville city, New Rochelle city, Newport Beach city, Newton city, Northbrook village, Norwalk city, Novato city, Novi city, Oak Park village, Orland Park village, Oro Valley town, Overland Park city, Palatine village, Palm Desert city, Palm Springs city, Palo Alto city, Paramus borough, Park Ridge city, Pasadena city, Plano city, Plantation city, Pleasant Hill city, Pleasanton city, Plymouth city, Poway city, Rancho Palos Verdes city, Redmond city, Redondo Beach city, Redwood City city, Richardson city, Rochester Hills city, Rockville city, Roswell city, San Carlos city, San Clemente city, San Dimas city, San Francisco city, San Juan Capistrano city, San Mateo city, San Rafael city, San Ramon city, Santa Clara city, Santa Clarita city, Santa Monica city, Saratoga city, Schaumburg village, Scottsdale city, Shaker Heights city, Shelton city, Shoreview city, Skokie village, Southfield city, St. Charles city, Stamford city, Strongsville city, Sugar Land city, Sunnyvale city, Thousand Oaks city, Torrance city, Troy city, Upland city, Upper Arlington city, Walnut Creek city, Watertown city, West Des Moines city, West Hollywood city, Westfield town, Westlake city, Wheaton city, White Plains city, Wilmette village, Woodbury city and Yorba Linda city.

Cities with initial log population beyond the threshold estimate ($\widehat{u}_n = 11.6639$) are Akron city, Albuquerque city, Amarillo city, Anaheim city, Anchorage municipality, Arlington CDP, Arlington city, Atlanta city, Aurora city, Austin city, Bakersfield city, Baltimore city, Baton Rouge city, Birmingham city, Boise City city, Boston city, Bridgeport city, Buffalo city, Charlotte city, Chattanooga city, Chesapeake city, Chicago city, Chula Vista city, Cincinnati city, Cleveland city, Colorado Springs city, Columbus city, Corpus Christi city, Dallas city, Dayton city, Denver city, Des Moines city, Detroit city, Durham city, El Paso city, Evansville city, Flint city, Fort Lauderdale city, Fort Wayne city, Fort Worth city, Fremont city, Fresno city, Garden Grove city, Garland city, Gary city, Glendale city, Glendale city, Grand Rapids city, Greensboro city, Hampton city, Hartford city, Hialeah city, Hollywood city, Honolulu CDP, Houston city, Huntington Beach city, Huntsville city, Irving city, Jackson city, Jersey City city, Kansas City city (KS), Kansas City city (MO), Knoxville city, Lakewood city, Lansing city, Las Vegas city, Lincoln city, Little Rock city, Long Beach city, Los Angeles city, Lubbock city, Madison city, Memphis city, Mesa city, Miami city, Milwaukee city, Minneapolis city, Mobile city, Modesto city, Montgomery city, Moreno Valley city, Nashville-Davidson, New Haven city, New Orleans city, New York city, Newark city, Newport News city, Norfolk city, Oakland city, Oceanside city, Oklahoma City city, Omaha city, Ontario city, Orlando city, Oxnard city, Pasadena city, Pasadena city, Paterson city, Philadelphia city, Phoenix city, Pittsburgh city, Plano city, Pomona city, Portland city, Providence city, Raleigh city, Reno city, Richmond city, Riverside city, Rochester city, Rockford city, Sacramento city, Salt Lake City city, San Antonio city, San Bernardino city, San Diego city, San Francisco city, San Jose city, Santa Ana city, Savannah city, Scottsdale city, Seattle city, Shreveport city, Spokane city, Springfield city (MA), Springfield city (MO), St. Louis city, St. Paul city, St. Petersburg city, Sterling Heights city, Stockton city, Sunnyvale city, Syracuse city, Tacoma city, Tallahassee city, Tampa city, Tempe city, Toledo city, Topeka city, Torrance city, Tucson city, Tulsa city, Virginia Beach city, Warren city, Washington city, Wichita city, Winston-Salem city, Worcester city and Yonkers city.

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Table 1: MEANS AND STANDARD DEVIATIONS, CITY VARIABLES IN 1990

| Variable | Mean | Stand. dev. |
|---|---|---|
| Population Growth (ln scale), 1990-2000 | 0.14 | 0.20 |
| Per Capita Income Growth (ln scale), 1989-1999 | 0.38 | 0.10 |
| Urban sprawl | | |
| Land Area Growth (ln scale), 1990-2000 | 0.09 | 0.14 |
| Population per Square Mile | 3618.33 | 3376.04 |
| Median Travel Time to Work (in minutes) | 20.68 | 4.95 |
| Human capital variables | | |
| Percentage population 18 years and over: Some college or higher degree | 37.88 | 11.77 |
| Percentage population 18 years and over: High school graduate (includes equivalency) or higher degree | 58.57 | 9.67 |
| Productive structure variables | | |
| Unemployment rate | 6.24 | 2.83 |
| Percentage employed civilian population 16 years and over: | | |
| Agriculture, forestry, fishing, and mining | 1.94 | 2.62 |
| Construction | 5.62 | 1.99 |
| Manufacturing (durable and nondurable goods) | 17.44 | 7.56 |
| Wholesale and Retail trade | 22.51 | 3.02 |
| Finance, insurance, and real estate | 7.08 | 2.62 |
| Educational, health, and other professional and related services | 24.19 | 6.75 |
| Public administration | 4.72 | 3.39 |
| Weather | | |
| Temperature index | 65.62 | 11.43 |

*Source:* 1990 and 2000 Census, www.census.gov

Table 2: PER CAPITA INCOME GROWTH

| Econometric Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Intercept | 0.5536*** | 0.9499*** | 2.4040*** | 2.4313*** |
| Variables | | | | |
| Per Capita Income (ln scale) in 1989 | -0.0183* | | | |
| Per Capita Income (ln scale) in 1989 $\leq u$ | | -0.0605*** | -0.1598*** | -0.1568*** |
| Per Capita Income (ln scale) in 1989 $> u$ | | -0.0553*** | -0.1536*** | -0.1509*** |
| Population in 1990 (ln scale) | | | | -0.0049 |
| Urban sprawl | | | | |
| Land Area Growth (ln scale) | | | 0.0951*** | 0.0911*** |
| Population per Square Mile (ln scale) | | | -0.0338*** | -0.0328*** |
| Median Travel Time to Work (in minutes) | | | 0.0007 | 0.0006 |
| Human capital variables | | | | |
| Percentage population 18 years and over: some college or higher degree | | | 0.0007 | 0.0007 |
| Percentage population 18 years and over: high school graduate (includes equivalency) or higher degree | | | 0.0021** | 0.0020** |
| Productive structure variables | | | | |
| Unemployment rate | | | -0.0016 | -0.0012 |
| Percentage employed civilian population 16 years and over: | | | | |
| Agriculture, forestry, fishing, and mining | | | -0.0023* | -0.0027** |
| Construction | | | -0.0079*** | -0.0081*** |
| Manufacturing (durable and nondurable goods) | | | -0.0018** | -0.0019** |
| Wholesale and Retail trade | | | -0.0049*** | -0.0050*** |
| Finance, insurance, and real estate | | | 0.0008 | 0.0009 |
| Educational, health, and other professional and related services | | | -0.0033*** | -0.0033*** |
| Public administration | | | -0.0031*** | -0.0032*** |
| Weather | | | | |
| Temperature index | | | -0.0025*** | -0.0025*** |
| Geographical dummy variables | | | | |
| Midwest Region | | | 0.0347*** | 0.0357*** |
| South Region | | | 0.0581*** | 0.0600*** |
| West Region | | | 0.0458*** | 0.0477*** |
| F-test | 3.50 | 11.49 | 26.19 | 25.00 |
| Adjusted R2 | 0.0030 | 0.0176 | 0.2896 | 0.2902 |

*Note:* Dependent variable: Per Capita Income growth 1989-1999 (ln scale). ***Significant at the 1% level **Significant at the 5% level *Significant at the 10 % level

Table 3: POPULATION GROWTH

| Econometric Models | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Intercept | 0.9803*** | 1.2703*** | 1.8930*** | 3.8341*** |
| Variables | | | | |
| Population in 1990 (ln scale) | -0.0706*** | | | |
| Population in 1990 (ln scale) $\leq u$ | | -0.1048*** | -0.0477*** | -0.0458*** |
| Population in 1990 (ln scale) $> u$ | | -0.0902*** | -0.0395*** | -0.0381*** |
| Per Capita Income (ln scale) in 1989 | | | | -0.2090*** |
| Urban sprawl | | | | |
| Land Area Growth (ln scale) | | | 0.4892*** | 0.4656*** |
| Population per Square Mile (ln scale) | | | -0.0724*** | -0.0767*** |
| Median Travel Time to Work (in minutes) | | | 0.0068*** | 0.0080*** |
| Human capital variables | | | | |
| Percentage population 18 years and over: some college or higher degree | | | 0.0083*** | 0.0099*** |
| Percentage population 18 years and over: high school graduate (includes equivalency) or higher degree | | | -0.0073*** | -0.0059*** |
| Productive structure variables | | | | |
| Unemployment rate | | | -0.0083*** | -0.0135*** |
| Percentage employed civilian population 16 years and over: | | | | |
| Agriculture, forestry, fishing, and mining | | | 0.0038* | 0.0049** |
| Construction | | | 0.0008 | -0.0005 |
| Manufacturing (durable and nondurable goods) | | | -0.0052*** | -0.0049*** |
| Wholesale and Retail trade | | | -0.0059*** | -0.0097*** |
| Finance. insurance. and real estate | | | -0.0050* | 0.0015 |
| Educational, health, and other professional and related services | | | -0.0114*** | -0.0134*** |
| Public administration | | | -0.0069*** | -0.0079*** |
| Weather | | | | |
| Temperature index | | | -0.0017*** | -0.0009 |
| Geographical dummy variables | | | | |
| Midwest Region | | | -0.0466*** | -0.0543*** |
| South Region | | | -0.0156 | -0.0389** |
| West Region | | | 0.0131 | -0.0118 |
| F-test | 104.31 | 69.52 | 69.80 | 71.38 |
| Adjusted R2 | 0.0809 | 0.1045 | 0.5269 | 0.5452 |

*Note:* Dependent variable: Population growth 1990-2000 (ln scale). ***Significant at the 1% level **Significant at the 5% level *Significant at the 10 % level

Table 4: SUMMARY TABLE

| Variable | All sample | Top income group | Top population group |
|---|---|---|---|
| Population Growth (ln scale) 1990-2000 | 0.14 | 0.18 | 0.09 |
| Per Capita Income Growth (ln scale) in 1989-1999 | 0.38 | 0.39 | 0.36 |
| Urban sprawl | | | |
| Land Area Growth (ln scale) | 0.09 | 0.06 | 0.06 |
| Population per Square Mile (ln scale) | 3618.33 | 3939.07 | 4443.91 |
| Median Travel Time to Work (in minutes) | 20.68 | 24.27 | 21.17 |
| Human capital variables | | | |
| Percentage population 18 years and over: some college or higher degree | 37.88 | 52.78 | 36.91 |
| Percentage population 18 years and over: high school graduate (includes equivalency) or higher degree | 58.57 | 68.64 | 56.57 |
| Productive structure variables | | | |
| Unemployment rate | 6.24 | 3.59 | 7.34 |
| Percentage employed civilian population 16 years and over: | | | |
| Agriculture, forestry, fishing, and mining | 1.94 | 1.36 | 1.58 |
| Construction | 5.62 | 5.24 | 5.48 |
| Manufacturing (durable and nondurable goods) | 17.44 | 15.75 | 15.53 |
| Wholesale and Retail trade | 22.51 | 20.96 | 21.67 |
| Finance. insurance. and real estate | 7.08 | 10.28 | 7.41 |
| Educational, health, and other professional and related services | 24.19 | 25.32 | 24.83 |
| Public administration | 4.72 | 3.62 | 5.45 |
| Weather | | | |
| Temperature index | 65.62 | 68.58 | 67.56 |
| Geographical dummy variables | | | |
| Northeast Region | 13.28% | 11.66% | 11.41% |
| Midwest Region | 28.60% | 28.83% | 20.13% |
| South Region | 27.57% | 15.95% | 35.57% |
| West Region | 30.55% | 43.56% | 32.89% |

*Note:* Average values of the variables under study across 1,175 observations (All sample), across the top per-capita income group (163 observations) and across top population group (149 observations).