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ORIGINAL ARTICLE

Cross-sectional growth in US cities from 1990 to 2000

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Abstract This paper analyses the growth of American cities, understood as the growth of the population or of the per capita income, from 1990 to 2000. This empirical analysis uses data from all the cities (incorporated places) with more than 25,000 inhabitants in the year 2000 (1,152 cities). The results show that while common convergence behaviour is observed in both population and per capita income growth, there are differences in the evolution of the distributions: the population distribution remains almost unchanged, while the per capita income distribution makes a great movement to the right. We use two different methodologies to test cross-sectional convergence across cities: linear growth models (allowing for spatial spillovers between locations) and spatial quantile regressions. We find evidence of significant spatial effects and nonlinear behaviour.

Keywords City growth · Linear model · Spatial lag model · Spatial error model · Spatial quantile regression

JEL Classification R00 · R11 · R12

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1 Introduction

Jacobs (1969) was the first to suggest that cities are the basic economic units of each country when she stated that 'cities are also primary economic organs'. Later, other writers would argue the same (Quigley 1998; Duranton 2000; Fujita and Thisse 2002).[1] Indeed, some very special characteristics coincide in the city as an economic unit. First, among cities there is complete freedom of movement in labour and capital (they are completely open economies). In addition, it is in cities that knowledge spillovers are most easily generated and transmitted, as documented both at the theoretical level (Loury 1979; Garicano and Rossi-Hansberg 2006) and at the empirical level (Glaeser et al. 1992; Henderson et al. 1995). Finally, the New Economic Geography adds that cities are a source of agglomeration economies (Duranton and Puga 2004).

The starting point for this work is the idea that the city has a double nature, on the one hand as a population centre and on the other as an engine of economic growth, and that the different external effects generated in cities can potentially have different effects on the population growth and per capita income growth. In particular, this paper analyses the cross-sectional growth of American cities, understood as growth of the population or per capita income, from 1990 to 2000, including variables to control for the main determinants of growth.

The American case has already been dealt with in earlier literature, using different econometric techniques and considering different periods and sample sizes. The two most direct precedents are Glaeser et al. (1995) and Glaeser and Shapiro (2003). Glaeser et al. (1995) examine the urban growth patterns in the 200 most populous cities in the US between 1960 and 1990 in relation to various urban characteristics in 1960. They show that the income and population growth are positively related to initial schooling, negatively related to initial unemployment, and negatively related to the initial share of employment in manufacturing. Glaeser and Shapiro (2003), using a larger sample size (they imposed a minimum population threshold of 25,000 inhabitants, considering the 1,000 most populous cities), and conclude that this behaviour would have continued during the decade 1990–2000. During this decade, the three most relevant variables would be human capital, individuals' transport systems (public or private), and climate. The latter variable points out the important role played by geography in cities' per capita income or population growth. Glaeser and Shapiro (2003) find that people moved to warmer, drier places. Moreover, in related work, Glaeser et al. (2001) argue that the correlation between weather and growth is evidence of the growing importance of consumers, relative to producers, in determining the location of cities. Therefore, a consumer city view would predict that weather variables would become more important in the 1990s. Black and Henderson (1998) conclude that the extent of city growth and mobility is related to natural advantage, or geography. Beeson et al. (2001) show that access to transportation networks, either natural (oceans) or produced (railroads), was an important source of growth over

[1] A good commentary on the relationship between cities and national economic growth can be found in Polèse (2005).

the period 1840–1990 and that weather is one of the factors promoting population growth. Furthermore, Mitchener and McLean (2003) find that some physical geography characteristics account for a high proportion of the differences in state productivity levels.

Other empirical studies exist analysing the growth of the American population and per capita income, although the geographical unit analysed is not the city. At the county level, Beeson et al. (2001) study the evolution of the population from 1840 to 1990, while Young et al. (2008) analyse the evolution of the income distribution from 1970 to 1998. Mitchener and McLean (2003) use data beginning in 1880 to study the variations among states in labour productivity. Finally, Yamamoto (2008) examines the disparities in per capita income in the period 1955–2003 using different geographical levels (counties, economic areas, states, and regions).

Furthermore, studies about the evolution of income distribution in the United States in terms of β-convergence have a long tradition. Barro and Sala-i-Martin (1992), Evans and Karras (1996a, b), Sala-i-Martin (1996), and Evans (1997) find statistically significant β-convergence effects using US state-level data, and Higgins et al. (2006) use US county-level data to document statistically significant β-convergence effects across the USA. Johnson and Takeyama (2001) use regression trees to examine the role of initial conditions in the economic development of the US statessince 1950, allowing the members of a large set of potentially important initial conditions to define convergence clubs in per capita income among the states. However, one fundamental issue is missing in all of these studies: the spatial dimension. Rey and Montouri (1999) were the first to adopt a spatial econometric perspective to study the US state income convergence over the 1929–1994 period, finding strong patterns of both global and local spatial autocorrelation. In recent research, Heckelman (2013) also finds significant spatial effects in US states for per capita income from 1930 to 2009.[2]

The next section presents the data used. We follow a two-step strategy. First, in Sect. 3, we determine whether the city population and city per capita income distributions followed similar paths in the 1990s. The results show that, while similar convergence behaviour is observed in both population and per capita income growth, there are differences in the evolution of the distributions: the population distribution remains almost static, while the per capita income distribution makes a great movement to the right. Second, to try to explain the differentiated behaviours observed in the evolution of the distributions of cities' per capita income and population, we examine the relationship between the initial urban characteristics in 1990 and the city growth (both in population and in per capita income) using two empirical methodologies; in Sect. 4, we estimate cross-sectional linear models allowing the existence of spatial effects between locations; and in Sect. 5, a spatial quantile regression model is used. The work ends with our conclusions.

[2] See Le Gallo et al. (2003) for a similar exercise of spatial econometric analysis of convergence across European regions.

2 Data description

We use data for all the cities in the USA with more than 25,000 inhabitants in the year 2000 (1,152 cities). The data come from the censuses[3] for 1990 and 2000. We identify cities as what the US Census Bureau calls incorporated places. The US 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 in 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.

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 the 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 eliminate cities that either more than doubled their land area or lost more than 10 % of their land area.[4] This correction eliminates extreme cases in which the city in 1990 is very different from the city in 2000.

The explanatory variables chosen are similar to those in other studies on city growth in the USA 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 al. 1995; Glaeser and Shapiro 2003). Table 1 presents the variables, which can be grouped into four types: urban sprawl variables, human capital variables, productive structure variables, and geographical variables.

The urban sprawl variables are basically intended to reflect the effect of city size on urban growth. For this, we use the population density (inhabitants per square mile), the growth in land area from 1990–2000 (as a control for the change in boundaries), and the variable median travel time to work (in minutes), representing the commuting cost borne by workers. The commuting time is endogenous and depends in part on the spatial organisation of cities and the location choice within cities. The median commuting time may reflect traffic congestion in larger urbanised areas, but might also reflect the size of the city in less densely populated areas or the remoteness of the 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 the costs in terms of the time taken by individuals to travel from home to work.

Regarding human capital, many studies demonstrate the influence of human capital on city size, as cities with better-educated inhabitants tend to grow more. We take the percentage of the population aged 18 years and over who are high school graduates (including equivalency) or have a higher degree. This variable represents a wide concept of human capital.

The third group of variables, referring to the productive structure, contains the unemployment rate and a measure of the diversity of the sectoral structure of the cities. We calculate the following diversity index:

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

[4] The land area data also come from the US Census Bureau: http://www.census.gov/population/www/censusdata/places.html and http://www.census.gov/geo/www/gazetteer/places2k.html.

Table 1 Means and standard deviations, city variables in 1990

Variable	Mean	SD
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	3,642.07	3,399.70
Median travel time to work (in minutes)	20.56	4.86
Human capital variable		
Percentage of population aged 18 years and over: high school graduate or higher degree	58.54	9.63
Productive structure variables		
Unemployment rate	6.26	2.81
Urban diversity index	0.83	0.03
Weather		
Temperature index	65.44	11.38
Percentage of water area	0.09	0.34
Annual precipitation (inches)	35.15	14.47

Sources: 1990 and 2000 Censuses, www.census.gov

$$\text{Urban diversity} = 1 - \sum_{m=1}^{M}\left(\frac{E_{mk}}{\sum_{m=1}^{M} E_{mk}}\right)^2.$$

The index is one minus the Herfindahl index in terms of the employment in the main productive sectors in city k, representing the degree of industrial diversity in that city; E_{mk} is the employment in each sector. The value of the urban diversity index is between zero and one. As the value becomes closer to one, the city industries become more diverse. We consider the percentage of the employed civilian population aged 16 years and over in the following sectors: the primary sector (agriculture, forestry, fishing and hunting, and mining), construction, manufacturing (durable and non-durable goods), wholesale and retail trade, finance, insurance, real estate; education, 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 kinds. We use two measures of weather:[5] annual precipitation (inches) and a temperature index. The temperature discomfort index (TEMP_INDEX) represents each city's climate amenity and is constructed as in Zheng et al. (2009) or Zheng et al. (2010). It is defined as:

[5] 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).

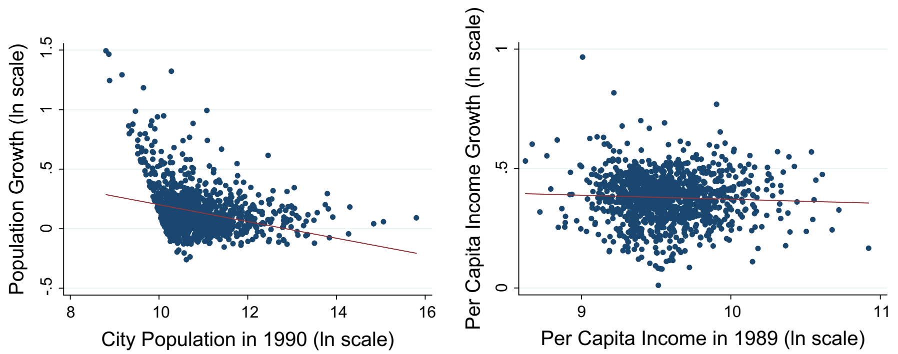

Fig. 1 Scatter plots of city growth (ln scale) against the initial level. *Note* Line fitted as $(\ln y_{it} - \ln y_{it-1}) = \alpha + \beta \ln y_{it-1}$. *Data source:* 1990 and 2000 Censuses, www.census.gov

$$\mathrm{TEMP\_INDEX}_k = \sqrt{(\mathrm{Winter\_temperature}_k - \min(\mathrm{Winter\_temperature}))^2 + (\mathrm{Summer\_temperature}_k - \max(\mathrm{Summer\_temperature}))^2}.$$

It represents the distance of the *k*-city's winter and summer temperatures from the mildest of the winter and summer temperatures across the 1,152 cities. A higher TEMP_INDEX means a harsher winter or a hotter summer, which makes the city a harder place in which to live. Additionally, information on the city's percentage of water area, related to the city's natural environment, is also considered.

Finally, we include several dummies that provide information about the geographic location, and which take the value one depending on the region (northeast region, midwest region, south region, or west region) in which the city is located.[6] 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). One potential problem is that these differences are hardly exogenous (unlike factors such as rainfall and temperature). These structures themselves are the results of the previous round of economic and productive activities; in other words, structures and agency are mutually constituted (see Plummer and Sheppard 2006).

3 Population and per capita income: twin paths or not?

Our first step is to determine whether the city population and city per capita income distributions followed similar paths in the 1990s. Figure 1 shows scatter plots of the city population growth and city per capita income growth (logarithmic scale) against the initial levels in 1990 and 1989. We use data from all the incorporated places with more than 25,000 inhabitants in the year 2000: 1,152 cities.

[6] We also introduce state-level dummies into some of the preliminary estimations, but most of them are not significant and the results are qualitatively the same.

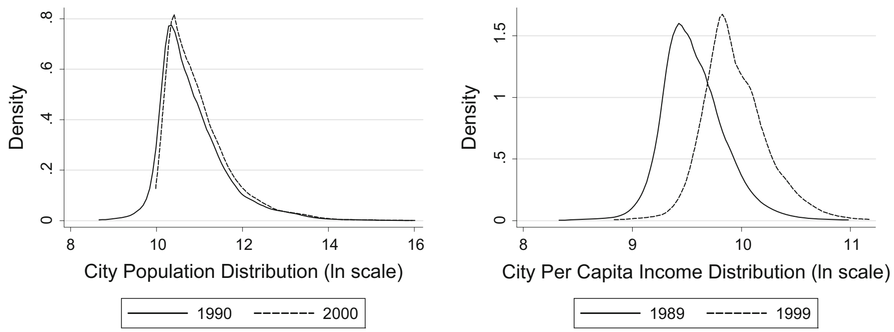

Fig. 2 Kernel density estimation (ln scale) of city per capita income and city population distributions. *Data source:* 1990 and 2000 Censuses, www.census.gov

We can observe that in both cases there is a negative relationship between the initial level and the growth rate. This implies that a larger initial population or per capita income means less growth (convergence growth). This negative effect is greater in the case of population growth than in the case of per capita income growth. Thus, while the slope β of the line adjusted with OLS in the case of population growth is a clearly significant and negative coefficient (−0.070), with the per capita income growth this coefficient (−0.016) is significantly different from zero only at the 10 % level, not the 5 % level. Moreover, the income's growth rates present a higher variance.

We would expect this convergent behaviour to have consequences for the evolution of distributions. Figure 2 shows the estimated empirical distributions using an adaptive kernel of city size, whether in per capita income or in population. It highlights an important change in the distribution of the city per capita income. The negative relationship observed earlier between initial city per capita income and growth, which we can identify with convergent growth, has clearly produced a rightwards displacement of the distribution.[7] Meanwhile, there is hardly any change in the population distribution of the cities, even though there was also a negative relationship between the initial population and the growth rate. Therefore, despite the common convergence evolution observed in the growth of both population and per capita income, there are differences in the evolution of the distributions; the population distribution remains almost static, while the per capita income distribution makes a great movement to the right.

Finally, we would like to determine the relationship between population growth and income growth. Accordingly, we construct the distributions of the population and per capita income growth rates, and then we study how they are related (Ioannides and Overman 2004). Figure 3 shows the stochastic kernel estimations of the distribution of population growth conditional on the distribution of per capita income growth. The contour plot is also shown, to simplify the interpretation. This figure shows the well-known positive relationship in large cities between per capita

[7] Everything seems to indicate that this behaviour has persisted for decades. Figure 2 of Young et al. (2008), corresponding to the evolution of the distribution of US counties' log per capita incomes from 1970 to 1998, presents a very similar effect to that observed in our estimated kernel of city per capita income distribution from 1989 to 1999.

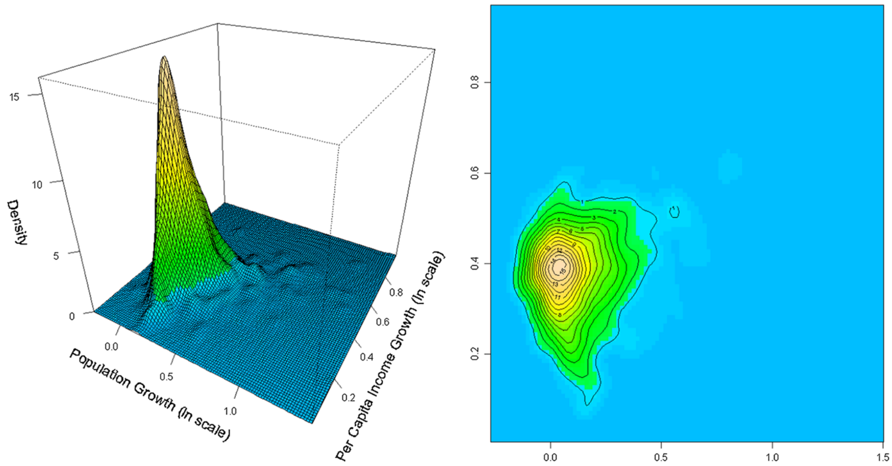

Fig. 3 Stochastic kernel estimates of the relationship between per capita income growth (ln scale) and population growth (ln scale). *Data source:* 1990 and 2000 Censuses, www.census.gov

income and city growth. There is an extensive literature reporting the benefits of urban agglomeration on city income or productivity;[8] see the surveys on this subject by Puga (2010) and Rosenthal and Strange (2004).

However, the differentiated behaviour observed in the evolution of the distributions of cities' per capita income and population could corroborate our initial idea: the different external effects generated in cities may produce different effects on population growth and per capita income growth. Therefore, the next sections analyse the cross-sectional growth in US cities controlling for the initial city characteristics in 1990, both in population and in per capita income, using different approaches.

4 Linear models

In this section, we estimate linear models that relate the growth in population or per capita income to a vector of initial city characteristics. Population growth can be described by this general equation:

$$\mathrm{Log}\left(\frac{N_{it+1}}{N_{it}}\right) = \alpha + \gamma' X_{ik} + \zeta_{it}, \tag{1}$$

where N_{it} is city i's population at time t. Thus, the dependent variable is the logarithmic growth rate, α is a constant, X_{ik} is the vector of city characteristics, γ is the vector of parameters describing the marginal effect of these explanatory variables, and ξ_{it} is the error term.

Theoretical economic foundations for this kind of linear equation can be found in the model of urban growth put forward by Glaeser et al. (1995) and further explicated by Glaeser (2000) and Glaeser and Shapiro (2003). This is a model of

[8] Although there is a great deal of variability in the results reported in the literature, see the meta-analysis by Melo et al. (2009).

spatial equilibrium similar to the Roback (1982) model, in which 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.

However, Eq. (1) does not allow spillover effects between cities. Such effects are plausible and highly likely when cities are close to one another (the cities are not autonomous economic or demographic units). Another source of possible spatial bias in the OLS regressions could be the spatial autocorrelation in the residuals. Overall, the spatial effects could be an important issue; for the US case, Rey and Montouri (1999) and Heckelman (2013) find significant spatial effects at the state level. Therefore, we apply the robust Lagrange multiplier and Moran's I tests to the residuals of the OLS regressions of the model in Eq. (1). If significant spatial effects are found, we estimate a spatial error model and a spatial autoregressive model with the aim of explicitly considering the impact of neighbouring locations on population growth.[9] The spatial error model extends model (1) by considering an error variable that satisfies

$$\xi_{it} = \lambda W \xi_{it} + v_{it},$$

with $|\lambda| < 1$ being a parameter that reflects the effect of the residuals of neighbouring variables on the residual of city i, W a weighting matrix that measures the distances between the different locations, and v_{it} an iid random variable that describes the error of the regression model. Different possibilities exist for choosing W; we consider an inverse distance weights matrix obtained from the coordinates (longitude and latitude)[10] of the locations in order to construct the Euclidean distance between the cities.[11] The spatial autoregressive model considers the following econometric specification:

$$\mathrm{Log}\left(\frac{N_{it+1}}{N_{it}}\right) = \alpha + \rho W \mathrm{Log}\left(\frac{N_{it+1}}{N_{it}}\right) + \gamma' X_{ik} + \zeta_{it}, \tag{2}$$

with $|\rho| < 1$ measuring the effect on the response variable of population growth in neighbouring cities.[12] The estimation of spatial models is carried out using maximum likelihood (ML) techniques under the assumption that the error variables are normally distributed.

Table 2 displays the OLS estimates of Eq. (1) and the ML estimates of the spatial models. The interpretation of the coefficients is easy; they measure the impact of the variables on logarithmic point growth (which can be approximated as percentage growth). We control for the initial per capita income in 1989 and for the city

[9] Fingleton and López-Bazo (2006) survey the literature on empirical growth models with spatial effects and conclude that most contributions focus their attention on the spatial lag and the spatial error models, neglecting the spatial cross-regressive specification.

[10] Spatial coordinates (longitude and latitude in decimal degrees) data for the incorporated places are obtained from the US Census Bureau Gazetteer.

[11] The spatial matrix was constructed using the SPATWMAT Stata command. The spatial regressions are estimated with the SPATDIAG and the SPATREG commands. All these tools for spatial data analysis using Stata were developed by Maurizio Pisati.

[12] The inclusion of the spatial lag in these OLS regressions can cause an endogeneity issue. We will deal with this potential problem in the next section.

Table 2 City population growth models

Variables	OLS linear models		Spatial error models		Spatial lag models	
	(1)	(2)	(3)	(4)	(5)	(6)
Urban sprawl						
Land area growth (ln scale)	0.407***	0.403***	0.422***	0.423***	0.416***	0.425***
Population per square mile (ln scale)	−0.049***	−0.047***	−0.060***	−0.061***	−0.053***	−0.054***
Median travel time to work (in minutes)	0.005***	0.005***	0.004***	0.004***	0.004***	0.003***
Human capital variable						
Percentage of population aged 18 years and over: high school graduate or higher degree	−0.001*	−0.001**	−0.001	−0.001	−0.001	−0.001
Productive structure variables						
Unemployment rate	−0.009***	−0.010***	−0.002	−0.002	−0.007***	−0.007***
Urban diversity index	0.259*	0.193	0.278**	0.261**	0.292**	0.231*
Weather						
Temperature index	−0.000	−0.002***	−0.001	−0.000	−0.001**	−0.002***
Percentage of water area	−0.018	−0.017	−0.021*	−0.021**	−0.011	−0.009
Annual precipitation (inches)	−0.001**	0.000	−0.000	−0.000	−0.001*	0.000
Controls						
Initial per capita income (ln scale) in 1989	−0.038	−0.031	0.033**	0.030*	−0.035	−0.032
City population growth rate 1980–1990 (ln scale)	0.346***	0.346***	0.343***	0.343***	0.343***	0.340***
Regions (geographical dummy variables)	No	Yes	No	Yes	No	Yes
λ			0.009***	0.011***		
ρ					0.001***	0.002***
Wald test of λ or $\rho = 0$			74.581	85.610	15.452	24.844
Moran's I test, p value			0.418	0.306		
Robust Lagrange multiplier test, p value			0.000	0.000	0.001	0.018

Table 2 continued

Variables	OLS linear models		Spatial error models		Spatial lag models	
	(1)	(2)	(3)	(4)	(5)	(6)
Log likelihood			841.854	844.151	768.299	782.542
R^2	0.603	0.610				
Observations	1,152	1,152	1,152	1,152	1,152	1,152

Endogenous variable: logarithmic population growth (1990–2000). All the specifications include a constant. The null hypothesis in the robust Lagrange multiplier and Moran's I tests is that there is zero spatial autocorrelation. *** Significant at the 1 % level, ** significant at the 5 % level, * significant at the 10 % level population growth rate in the previous period (1980–1990) in all the specifications. Some regressions include region dummies. Table 2 also reports the p values of the spatial tests. These p values provide mixed evidence of the statistical significance of the spatial effects for the spatial error model; the null hypothesis of zero spatial autocorrelation cannot be rejected with the Moran's I test, while the same null can be rejected with the robust Lagrange multiplier test. The robust Lagrange multiplier test also finds significant spatial autocorrelation with the spatial autoregressive model. Moreover, the Wald test confirms that the parameters λ and ρ are significant in both spatial models, and the log likelihood points to a better fit of the spatial error model.

If we consider the linear models without spatial effects (columns 1 and 2), the basic results, in general, show that the estimated coefficients for the variables are similar across the different models; the sign of the coefficients is consistent, although there are slight differences in the magnitude and significance. The results obtained in previous studies are confirmed. The initial per capita income is only significant in the spatial error model. The positive coefficient would indicate that thriving cities attract population. The past population growth rate (1980–1990) has a significant positive coefficient in all the specifications, confirming the high persistence of the growth rates of US cities (Glaeser and Shapiro 2003). The sign of the travel time coefficient is positive, although no theory of urban growth predicts that commuting time (that is, congestion) should have a positive effect on growth. A more plausible explanation for this result is that some relevant variables are missing. Cities that are more spread out have both more developable land (so that there is space for the construction of new homes and room for the city to grow) and also have a larger distance between the residential fringe and the central business district. The key omitted variable here would be the percentage of developable land.[13]

Surprisingly, the human capital variable becomes not significant when we introduce the spatial effects. As we will show later, human capital is more important to economic growth than to population growth. However, the unemployment rate has a significant negative coefficient (except in the spatial error model) and a clear interpretation: cities with high unemployment experience lower population growth rates. This would indicate migration across cities and transition to a spatial equilibrium. Regarding the diversity index, once we account for spatial effects, both the spatial error and the spatial lag models indicate a significant positive effect on population growth, with an estimated coefficient around 0.25. As higher values of the index represent more diverse productive structures, this result indicates that specialised economies grew less in population during the period.

Finally, the influence of geography on population growth is slight. The 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 is only significant in the spatial lag model. Precipitation is only significant in two cases (columns 1 and 5). The spatial error model also reveals a negative effect of the percentage of water area on growth.

[13] This is omitted because of data scarcity, although part of this variable could be captured by the city land area growth, which has already been included.

We also estimate Eq. (1) using city per capita income growth (y_{it}) as the dependent variable. Then, Eq. (1) changes to:

$$\text{Log}\left(\frac{y_{it+1}}{y_{it}}\right) = \eta + \beta \cdot \text{Log}(y_{it}) + \phi' Z_{ik} + \varepsilon_{it}, \tag{3}$$

the well-known expression of the conditional β-convergence (Evans 1997; Evans and Karras 1996a, b). η is a constant, Z_{ik} is a vector of variables that control for cross-city heterogeneity in determinants of the steady-state growth rate (we use exactly the same independent variables as in the population growth model), φ is a vector of coefficients, and v_{it} is a zero-mean finite-variance error. There are several theoretical economic growth models that can produce Eq. (2) at the state, county, or region level. For a neoclassical growth model, see Barro and Sala-i-Martin (1992).

The spatial alternatives to Eq. (3) are modelled in a similar fashion to the spatial population growth models explained above. The spatial error model extends model (3) by including an error variable that satisfies

$$\varepsilon_{it} = \lambda W \varepsilon_{it} + v_{it},$$

while the econometric specification of the spatial autoregressive model is the following:

$$\text{Log}\left(\frac{y_{it+1}}{y_{it}}\right) = \eta + \rho W \text{Log}\left(\frac{y_{it+1}}{y_{it}}\right) + \beta \cdot \text{Log}(y_{it}) + \varphi' Z_{ik} + \varepsilon_{it}. \tag{4}$$

Fingleton and López-Bazo (2006) provide theoretical foundations for both spatial models, based on two growth models with across-region externalities due to knowledge diffusion.

Table 3 presents the OLS estimates of Eq. (3), using the same exogenous variables as the population growth model (although the table structure is the same, in this model the initial city per capita income is the main explanatory variable and the rest are controls). The ML estimates of the spatial models and the p values of the spatial tests are also shown. Again, the p values provide mixed evidence of the statistical significance of the spatial effects for the spatial error model (Moran's I test cannot reject the no spatial autocorrelation null, while the same null can be rejected with the robust Lagrange multiplier test) and significant spatial effects with the spatial autoregressive model. However, this time, the Wald test rejects the significance of the ρ parameter at the 5 % level for the spatial lag model and the log likelihood again indicates a better fit of the spatial error model.

The estimate of the β-coefficient corresponding to the initial level of per capita income is negative and clearly significant in all the specifications, finding evidence in favour of convergence across cities, as in the previous section. The difference is that here, when controlling for cross-city heterogeneity, the coefficient is greater (around −0.07 instead of −0.016), indicating stronger convergence, which better describes the behaviour observed in the evolution of the distribution of city per capita income (Fig. 2).

Some of the coefficients in Table 3 keep the same sign as in the models for population growth—for example, urban diversity still has a positive (although less significant) effect on per capita income growth—but there are remarkable differences. First, it is

Table 3 City per capita income growth models

Variables	OLS linear models		Spatial error models		Spatial lag models	
	(1)	(2)	(3)	(4)	(5)	(6)
Urban sprawl						
Land area growth (ln scale)	0.135***	0.105***	0.119***	0.086***	0.139***	0.107***
Population per square mile (ln scale)	−0.039***	−0.031***	−0.034***	−0.025***	−0.042***	−0.031***
Median travel time to work (in minutes)	0.001	0.001	0.003***	0.003***	0.001	0.001
Human capital variable						
Percentage of population aged 18 years and over: high school graduate or higher degree	0.002***	0.002***	0.002***	0.002***	0.003***	0.002***
Productive structure variables						
Unemployment rate	−0.001	0.000	−0.002	−0.001	−0.001	0.001
Urban diversity index	0.166*	0.144	0.045	0.007	0.209**	0.154
Weather						
Temperature index	−0.002***	−0.003***	−0.002***	−0.003***	−0.002***	−0.003***
Percentage of water area	0.038***	0.040***	0.035***	0.037***	0.040***	0.041***
Annual precipitation (inches)	0.000	0.001**	−0.000	0.001*	0.000	0.001**
Controls						
Initial per capita income (ln scale) in 1989	−0.074***	−0.056***	−0.071***	−0.054***	−0.079***	−0.058***
City population growth rate 1980–1990 (ln scale)	−0.015	−0.012	−0.023*	−0.021*	−0.012	−0.011
Regions (geographical dummy variables)	No	Yes	No	Yes	No	Yes
λ			−0.001***	−0.001***		
ρ					0.001*	0.000
Wald test of λ or $\rho = 0$			10.639	13.396	2.960	0.211
Moran's I test, p value			0.355	0.255		
Robust Lagrange multiplier test, p value			0.000	0.000	0.001	0.000

Table 3 continued

Variables	OLS linear models		Spatial error models		Spatial lag models	
	(1)	(2)	(3)	(4)	(5)	(6)
Log likelihood			1,206.912	1,232.226	1,202.293	1,223.826
R^2	0.251	0.280				
Observations	1,152	1,152	1,152	1,152	1,152	1,152

Endogenous variable: logarithmic per capita income growth (1989–1999). All the specifications include a constant. The null hypothesis in the robust Lagrange multiplier and Moran's I tests is that there is zero spatial autocorrelation. *** Significant at the 1 % level, ** significant at the 5 % level, * significant at the 10 % level notable 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 basically the individual's movements rather than the city's productivity. A second important difference from the population growth results is that the human capital variable is significant and positive in all the models, revealing a positive influence of human capital on economic growth at the city level. This result coincides with those of other studies analysing the influence of education on city growth. Simon and Nardinelli (2002) analyse the period 1900–1990 for the US and conclude that the cities with higher average levels of human capital grew faster over the twentieth century, and Glaeser and Saiz (2004) study the period 1970–2000 and show that this is due to skilled cities being more economically productive (than less-skilled cities).

Third, physical geography seems to be more important to income growth than to population growth. Thus, the coefficient of the temperature index is again significant and negative, indicating that a higher index means that the city is a harder place in which to produce. The effect of the annual precipitation variable is positive but significant only in half of the estimations, and the percentage of water area is positive and significant in all the specifications. Both precipitation and water area are particularly intense in the northeast and midwest regions; the positive estimated coefficients indicate higher growth rates of the cities located in these regions.

5 Spatial quantile regressions

In this section, we use an alternative approach. One important issue with the previous estimations derived from linear models is the possible nonlinear behaviour. Some of the variation in city growth rates (both in population and in income) may reflect the fact that the influence of some city characteristics is not the same across the distribution of growth rates. To model these possible heterogeneous effects of city variables on the growth rate, we estimate quantile regressions accounting for spatial autocorrelation. Although there are not many studies applying this methodology to city or regional data, Zietz et al. (2008) and Kostov (2009) discuss the advantages of this approach in depth and apply it to hedonic models of house prices and land, respectively.

The quantile regression version of the linear spatial lag models shown in Eqs. (2) and (4) can be written as

$$\mathrm{Log}\left(\frac{N_{it+1}}{N_{it}}\right) = \alpha(\tau) + \rho(\tau) W \mathrm{Log}\left(\frac{N_{it+1}}{N_{it}}\right) + \gamma'(\tau) X_{ik} + \zeta_{it} \quad (5)$$

and

$$\mathrm{Log}\left(\frac{y_{it+1}}{y_{it}}\right) = \eta(\tau) + \rho(\tau) W \mathrm{Log}\left(\frac{y_{it+1}}{y_{it}}\right) + \beta(\tau) \cdot \mathrm{Log}(y_{it}) + \varphi'(\tau) Z_{ik} + \varepsilon_{it} \quad (6)$$

for population and per capita income growth, respectively. We still consider an inverse distance weights matrix obtained from the coordinates of the locations, but note that the parameters to estimate now are τ dependent, where τ is the corresponding quantile of the growth rate. As Kostov (2009) argues, quantile regressions

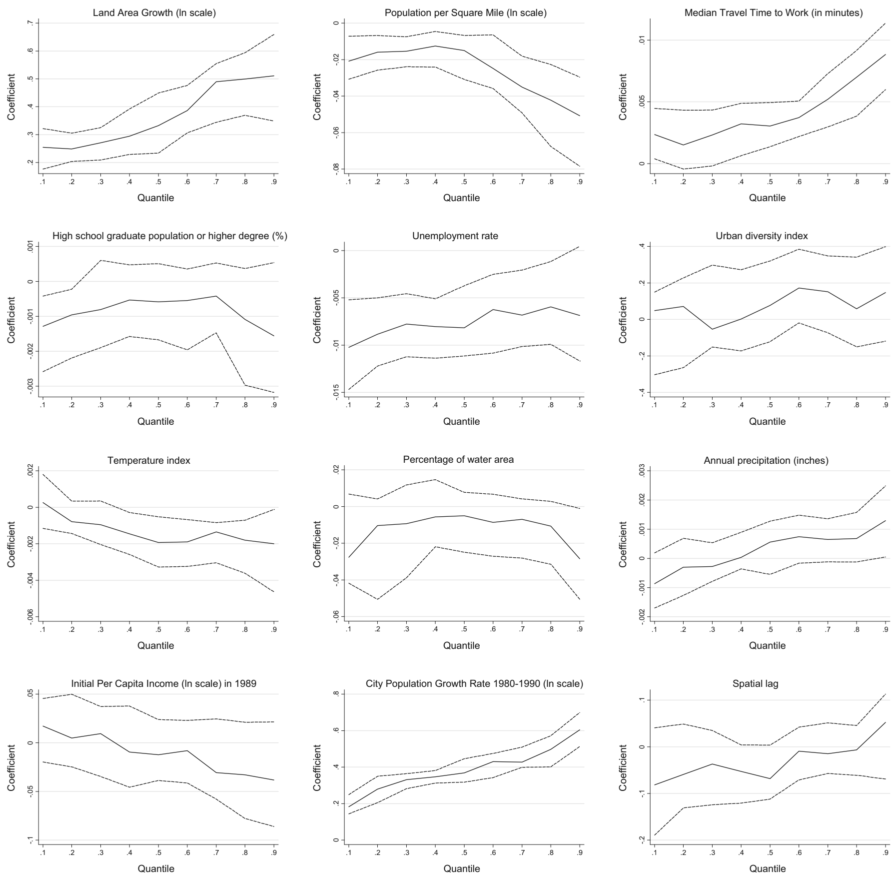

Fig. 4 Spatial quantile regression estimates, population growth model. *Note* Kim and Muller (2004) two-stage quantile regression results. Endogenous variable: logarithmic population growth (1990–2000). The model includes a constant and regional dummies. Bootstrap standard errors. The 95 % confidence intervals are based on the percentile method

take into account unobserved heterogeneity and allow for heteroscedasticity among the disturbances, including spatial error dependence.

The second main concern with the estimations in the previous section is the possible endogeneity issue. Including a spatial lag in an OLS regression can cause inference problems owing to the endogeneity of the spatial lag (Anselin 2001), and the same can apply to the quantile regressions. To deal with this issue, we use the Kim and Muller (2004) estimation procedure. This two-stage method uses the regressors and their spatial lags as instruments. The standard errors are calculated using a simple bootstrap estimator.[14]

Figure 4 shows the spatial quantile regression results for the population growth model of Eq. 5 (the estimated coefficients are presented in Table 4 in the "Appendix").

[14] The spatial quantile regressions are estimated using the McSpatial R package developed by Daniel McMillen.

The different graphs display the estimates of the coefficients and the confidence intervals for each explicative variable across the nine quantiles considered (τ ranges from 0.1 to 0.9). The estimated model also includes regional dummies (not shown).

Although the sign of the effects mostly coincides with the results obtained in the linear models estimated previously, the quantile regressions reveal interesting nonlinear behaviour. The effect of some variables increases for the higher quantiles; as expected, the variables measuring urban sprawl and congestion (land area growth and median travel time to work) have a greater effect on the higher-quantile cities. The same applies to the unemployment rate; the negative effect of unemployment on population growth is greater in the bottom quantile cities, meaning that the higher the unemployment rate, the lower the city population growth rate. The increasing effect of the past population growth rate on the highest quantile cities indicates that the persistence in the growth rates of US cities detected by Glaeser and Shapiro (2003) is higher than the linear model estimates revealed; the quantile estimates show that the effect of past growth is three times higher (the coefficient rises from 0.182 to 0.605) on the top quantile (0.9) than on the bottom quantile (0.1). The effect of the urban diversity index and precipitation on population growth also increases for the top quantiles, but the estimated effects are not significant. This is one of the differences from the linear model estimations, in which we find a significant positive effect of urban diversity on growth. The explanation could be an endogeneity issue in the previous estimations in Sect. 4, which is now corrected.

The effect of the other variables decreases for the cities with the highest population growth at the top quantiles (temperature index and initial income). In the other cases, the estimated effect follows an inverted *U*-shape pattern (population density, human capital, and water area). However, as in the linear models, the human capital variable is not significant in most of the quantiles (the exceptions are quantiles 0.1 and 0.2).

Regarding income growth, Fig. 5 reports the spatial quantile regression results for the per capita income growth model; see Eq. 6 (the estimated coefficients are shown in Table 5 in the "Appendix"). Again, we find clear nonlinear behaviour. The effect of some variables increases for the higher quantiles (land area growth, median travel time to work, unemployment rate, temperature index, water area, initial income, and past population growth), while the effect of other variables decreases for the cities with the highest income growth in the top quantiles (population density, urban diversity, and precipitation). The estimated coefficients of the initial income change from significantly negative for the bottom and middle quantile cities to non-significant for the top quantile, indicating strong income convergence across cities. Thus, for the lowest income growth cities, a high initial income has a clear negative effect on growth, while for the highest income growth cities the initial income has no significant effect. A kind of inverted *U*-shape pattern can also be found for the human capital variable, although it is less pronounced than in the population growth model. The estimated coefficient for the human capital measure is always positive and significant, but it is higher in the middle quantile cities. This suggests that the benefits of education are not equally distributed across cities.

Finally, the influence of the spatial lag is not significant in either of the two models for most of the quantiles; in the population growth model, the effect is increasing with the

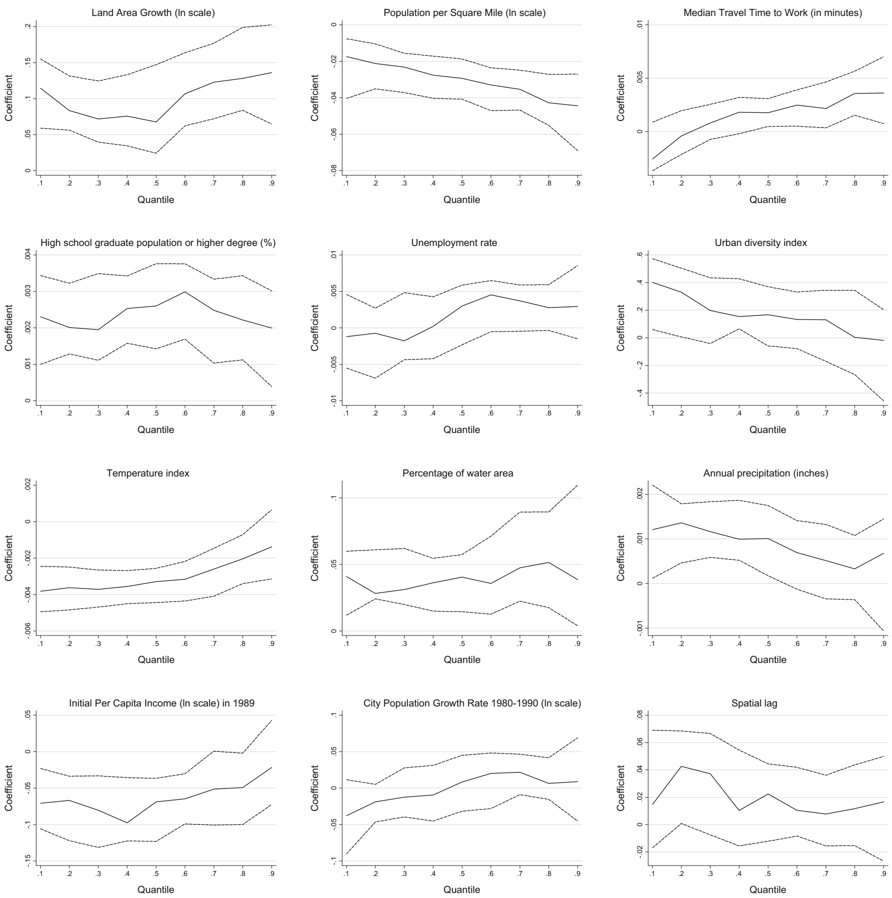

Fig. 5 Spatial quantile regression estimates, per capita income growth model. *Note* Kim and Muller (2004) two-stage quantile regression results. Endogenous variable: logarithmic per capita income growth (1989–1999). The model includes a constant and regional dummies. Bootstrap standard errors. The 95 % confidence intervals are based on the percentile method

quantile, while in the income model, the effect is decreasing with the quantile. Thus, we can reject the spatial lag dependence over most of the sample. Nevertheless, this does not mean the rejection of any kind of spatial dependence. On the contrary, the quantile regressions allow for heteroscedasticity among the disturbances, including spatial error dependence (Kostov 2009), and in the linear models estimated in Sect. 4, we have already found a better fit of the spatial error model than that of the spatial lag model.

6 Conclusions

This paper analyses the growth of American cities, understood as the growth of the population or the per capita income, from 1990 to 2000. One of the contributions of the paper is the analysis of cross-sectional growth at the city level, using data from all the cities (incorporated places) with more than 25,000 inhabitants in the year 2000 (1,152 cities). The descriptive results show that, while common convergence behaviour is observed in both population and per capita income growth, there are differences in the evolution of the distributions: the population distribution remains almost unchanged, while the per capita income distribution develops a great movement to the right.

Another contribution is that we use two different methodologies to try to explain these differentiated behaviours in the evolution of the population and income distributions: linear growth models and spatial quantile regressions, allowing for spatial spillovers between locations. By estimating linear models, we find significant evidence of high persistence in population growth rates and conditional β-convergence in per capita income across cities. We introduce several explanatory variables to control the initial city characteristics. Some of the results, similar to those of other studies, are that specialised economies grew less in population in the period, the unemployment rate has a clear negative influence on population growth (Glaeser et al. 1995) but no significant effect on income growth, the human capital variable is significant and positive in all the models, indicating a positive influence of human capital on economic growth (Glaeser et al. 1995; Simon and Nardinelli 2002; Glaeser and Shapiro 2003), and the weather variables (physical geography) seem to have a greater impact on income growth than on population growth (Black and Henderson 1998; Glaeser et al. 2001; Glaeser and Shapiro 2003). We also find significant spatial effects at the city level and our empirical results favour the spatial error model specification rather than the spatial lag model.

The spatial quantile regressions allow us to test nonlinear behaviour and correct the possible endogeneity issues of the spatial lag. We use the Kim and Muller (2004) estimation procedure, a two-stage method that uses the regressors and their spatial lags as instruments. Although the signs of the effects mostly coincide with the results obtained in the linear models, there are some exceptions. For example, we do not find a significant effect of urban diversity on growth. Moreover, we find clear nonlinear behaviours in both population and income growth. These nonlinearities indicate that the persistence in population growth and the income convergence across cities are stronger than indicated by the linear models.

However, these results can be improved in several ways. First, beneath the overall cross-sectional convergence there could be different spatial regimes (Beaumont et al. 2003). Thus, the linear models can be extended to account for convergence clubs (Durlauf and Johnson 1995). Second, we could quantify how much of the spatial pattern of per capita income can be attributed to exogenous first-nature factors alone and how much is a consequence of endogenous second-nature elements (Roos 2005; Chasco et al. 2012). To carry out this analysis, we would need more data, specifically to improve the information on first-nature indicators. Both questions clearly deserve further research.

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Appendix

See Tables 4 and 5.

Table 4 Spatial quantile regression estimates, population growth model

Variables	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Urban sprawl									
Land area growth (ln scale)	0.255***	0.248***	0.271***	0.295***	0.332***	0.386***	0.49***	0.499***	0.511***
Population per square mile (ln scale)	−0.021***	−0.016***	−0.015***	−0.012**	−0.015**	−0.025***	−0.035***	−0.042***	−0.051***
Median travel time to work (in minutes)	0.002**	0.002	0.002*	0.003***	0.003***	0.004***	0.005***	0.007***	0.009***
Human capital variable									
Percentage of population aged 18 years and over: high school graduate or higher degree	−0.001**	−0.001*	−0.001	−0.001	−0.001	−0.001	−0.000	−0.001	−0.002
Productive structure variables									
Unemployment rate	−0.010***	−0.009***	−0.008***	−0.008***	−0.008***	−0.006***	−0.007***	−0.006***	−0.007**
Urban diversity index	0.049	0.071	−0.054	0.003	0.077	0.172	0.152	0.058	0.147
Weather									
Temperature index	0,000	−0.001	−0.001	−0.001**	−0.002***	−0.002***	−0.001**	−0.002**	−0.002*
Percentage of water area	−0.028*	−0.01	−0.009	−0.006	−0.005	−0.009	−0.007	−0.011	−0.028**
Annual precipitation (inches)	−0.001*	−0.000	−0.000	0,000	0.001	0.001	0.001*	0.001	0.001**
Controls									
Initial per capita income (ln scale) in 1989	0.017	0.005	0.009	−0.01	−0.012	−0.008	−0.031	−0.033	−0.038
City population growth rate 1980–1990 (ln scale)	0.182***	0.279***	0.331***	0.346***	0.367***	0.43***	0.427***	0.497***	0.605***
Regions (geographical dummy variables)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial lag	−0.082	−0.059	−0.037	−0.053	−0.068*	−0.009	−0.015	−0.007	0.052

Kim and Muller (2004) two-stage quantile regression results. Endogenous variable: logarithmic population growth (1990–2000). The model includes a constant. Bootstrap standard errors. *** Significant at the 1 % level, ** significant at the 5 % level, * significant at the 10 % level

Table 5 Spatial quantile regression estimates, per capita income growth model

Variables	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Urban sprawl									
Land area growth (ln scale)	0.114***	0.083***	0.072***	0.076***	0.068**	0.107***	0.123***	0.128***	0.136***
Population per square mile (ln scale)	−0.017**	−0.021***	−0.023***	−0.028***	−0.029***	−0.033***	−0.035***	−0.043***	−0.044***
Median travel time to work (in minutes)	−0.003**	−0.000	0.001	0.002**	0.002**	0.002***	0.002**	0.004***	0.004**
Human capital variable									
Percentage of population aged 18 years and over: high school graduate or higher degree	0.002***	0.002***	0.002***	0.003***	0.003***	0.003***	0.002***	0.002***	0.002***
Productive structure variables									
Unemployment rate	−0.001	−0.001	−0.002	0.000	0.003	0.005**	0.004**	0.003	0.003
Urban diversity index	0.401***	0.331**	0.197	0.154	0.168	0.134	0.131	0.004	−0.018
Weather									
Temperature index	−0.004***	−0.004***	−0.004***	−0.004***	−0.003***	−0.003***	−0.003***	−0.002***	−0.001
Percentage of water area	0.041***	0.028***	0.031**	0.036***	0.041***	0.036**	0.047**	0.052***	0.039
Annual precipitation (inches)	0.001**	0.001***	0.001***	0.001***	0.001**	0.001*	0.001	0.000	0.001
Controls									
Initial per capita income (ln scale) in 1989	−0.071***	−0.067***	−0.081***	−0.098***	−0.069***	−0.065***	−0.051*	−0.049*	−0.022
City population growth rate 1980–1990 (ln scale)	−0.038	−0.019	−0.012	−0.009	0.008	0.02	0.022	0.006	0.009
Regions (geographical dummy variables)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial lag	0.015	0.043**	0.037*	0.010	0.022	0.010	0.008	0.012	0.017

Kim and Muller (2004) two-stage quantile regression results. Endogenous variable: logarithmic per capita income growth (1989–1999). The model includes a constant. Bootstrap standard errors. *** Significant at the 1 % level, ** significant at the 5 % level, * significant at the 10 % level

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