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Abstract: This paper reconsiders the path of the growth of American cities since 1790 (when the first census was published) in light of new theories of urban growth. Our null hypothesis for long-term growth is random growth, but the alternative is not only mean reversion as is usual. We obtain evidence supporting random growth against the alternative of mean reversion (convergence) in city sizes by using panel unit root tests, but we also examine mobility within the size distribution of cities to try to extract growth patterns different from the general unit root trend detected. We find evidence of high mobility when we model growth as a first-order Markov process. Finally, by using a cluster procedure, we find strong evidence in favour of conditional convergence in city growth rates within convergence clubs, which we interpret as "local" mean-reverting behaviours. We interpret the high mobility and the results of the clustering analysis as signs of a sequential city growth pattern toward a random growth steady state.

Keywords: city size, urban growth, random growth, sequential city growth, transition matrices, club convergence

JEL: C12, O18, R11, R12

1. Introduction

Several theories have been proposed in the literature to try to explain urban growth. Davis and Weinstein (2002) group traditional theoretical explanations into three main groups of theories: the existence of increasing returns to scale, the importance of locational fundamentals and random growth. Random growth theory is especially important from a long-term perspective, because the influence of other factors such as locational fundamentals and increasing returns may change (or even disappear) over time. Locational fundamentals are exogenous factors linked to the physical landscape, such as temperature, rainfall, access to the sea, the presence of natural resources and the availability of arable land. Random growth models usually assume that these characteristics are randomly distributed across space, but actually they are not. In terms of physical geography, factors such as mineral resources and nice weather are clearly concentrated in particular regions. For example, the nearby deposits of coal, iron ore and limestone as well as the extensive network of natural waterways and deep water sea and river ports contributed to the development of the United States manufacturing belt in the Upper Midwest and North-east regions (Berry and Kasarda, 1977).[1] However, while locational fundamentals may have played a crucial role in early settlements, one would expect their influence on urbanisation to decrease over time because of advances in transportation and communication technology.[2] By contrast, urban increasing returns, also known as agglomeration economies, appeared later as a consequence of industrial development. The empirical literature on agglomeration economies and their positive effects on urban growth is wide, although there is a great deal of variability in the results reported (see the meta-analysis by Melo et al. (2009)).

Nevertheless, there is some consensus in recent papers that empirically random growth can only hold as a long-run average; Gabaix and Ioannides (2004) indicate that "*the casual impression of the authors is that in some decades, large cities grow faster than small cities, but in other decades, small cities grow faster.*" Recently, new theories of urban growth have been developed to accommodate the observed different growth patterns over time. Cuberes (2011) concludes, by using a comprehensive cross-country dataset, that historically city growth may have been sequential. Sequential city growth means that cities have early periods of fast growth (from their date of entry as a city) followed by slow growth and/or stagnation. The idea is that during some periods, the largest cities that entered the distribution first are the ones that grow the fastest. Later, their growth slows, and the smaller cities that entered later are the ones that grow the fastest. When these reach a certain size, their growth rates slow again and other smaller cities are the ones that grow fastest, and so on. It should be noted that the result is convergence among cities. This convergence is not in size, as final city size is determined by other factors such as amenities, city productivity, land availability, etc., but in the growth rates at the steady state. Thus, random growth (similar growth rates independent of city size) appears as the steady state after the entry of new cities stops, while sequential city growth theory helps explain different growth patterns during the transition to the steady state and the effect of the entry of new cities.

To our knowledge, only two papers model sequential city growth: Henderson and Venables (2009) and Cuberes (2009).[3] The model developed by Henderson and Venables (2009) examines city formation in a country whose urban population is growing steadily over time, with new cities required to accommodate this growth. It yields the sequential formation of cities, where new cities grow from scratch to a stationary size. The basic assumptions of their model are that city formation requires investment in fixed capital in the form of housing and urban infrastructure and that agents are forward-looking. Cuberes (2009) presents another model of sequential city growth. In this model, increasing returns to scale constitute the force that favours the agglomeration of resources in a city, while the convex costs associated with the stock of installed capital represent the congestion force that limits city size. The key factor to generating sequential growth is the assumption of irreversible investment in physical capital.

This paper reconsiders the path of the growth of American cities since 1790, paying special attention to random growth and new sequential city growth theories. The urban system of the US has often been studied because of its special characteristics. First, it is a relatively young system compared with the European countries (the first census by the US Census Bureau dates from 1790) characterised by the entry of new cities (Dobkins and Ioannides, 2000). In addition, its inhabitants present very high geographic mobility; Cheshire and Magrini (2006) estimate that population mobility in the US is 15 times higher than that in Europe. Both characteristics, high migration flows and the entry of new cities, should reduce the time transition to spatial equilibrium between cities. In line with this, González-Val (2010) finds that the final decades of the twentieth century were characterised by stability in the number of cities and the percentage of the US total population they represent, indicating a shift to a more stable and less concentrated city size distribution. Finally, industry cycles have an important effect on the growth rates of American cities (Duranton, 2007). Consistent with this finding, in the second half of the nineteenth century and the early twentieth century, the growing urban population was concentrated in the North-eastern region known as the manufacturing belt, while in the second half of the twentieth century the rise of the Sun Belt (a phenomenon known as regional inversion; Lanaspa-Santolaria et al., 2002) attracted population to the West Coast area. The rise of the Sun Belt also included the growth of the South-eastern region of the US. Many Americans, foreign- and native-born, moved to Southern states (Texas, Florida and, more recently, Georgia, North Carolina and Virginia) in the latter part of the twentieth century, but the reason for these migration flows seems to be nice weather rather than industry cycles (Rappaport, 2007). In addition, the South-western states of Arizona and Nevada have also been growing rapidly because of both domestic and international migration (Massey, 2008; Iceland, 2009).

Many papers study the long-term path of American urban growth. These include Dobkins and Ioannides (2000, 2001), Kim (2000), Beeson et al. (2001), Overman and Ioannides (2001), Black and Henderson (2003), Ioannides and Overman (2003), Kim and Margo (2004), González-Val (2010) and Michaels et al. (2012). The spatial units (states, counties, minor civil divisions, metropolitan areas, incorporated places, etc.) and time periods studied and statistical and econometric methods used in the literature vary widely. Our study differs from previous studies in two main points. First, we analyse the path of the largest American cities from the beginning of the urban system in 1790, while most studies only consider the twentieth century. Such a wide time horizon enables us to consider the effect of the entry of new cities (most of them during the nineteenth century) and to look for different patterns of city growth. Second, we consider random growth as the long-run average, but the alternative is not only mean reversion as is usual: we use different methodologies to capture possible different growth patterns from the overall random growth behaviour.

The next section presents the data used. Our basic hypothesis for long-term growth is random growth. We use random growth as a benchmark because the effect of other factors (locational fundamentals or increasing returns) may change over time when such a long period is considered, for instance, owing to the decrease in transport costs (Davis and Weinstein, 2002). Moreover, among others, Ioannides and Overman (2003) and

González-Val (2010) find that random growth is a good description of city size growth in the US during the twentieth century. Therefore, in Section 3 we test random growth versus mean reversion (convergence) in US cities by using panel unit root tests. We obtain evidence supporting random growth against the alternative of mean reversion in city sizes. In Section 4, we examine intra-distribution mobility to try to extract growth patterns that are different from the general unit root trend. We use two techniques. First (Section 4.1), we calculate transition matrices, which tell us the degree of mobility in terms of probability, by applying a generalised equation to enable cities to enter and leave the sample. We interpret mobility in terms of transition probabilities within the distribution of the relative positions of cities, modelling growth as a first-order Markov process. Second (Section 4.2), we apply a cluster algorithm to identify different groups of cities that converge with each other. The results point to a certain type of sequential growth, at least within groups. We discuss the different empirical results and conclude in Section 5.

2. Data

There are various ways of defining a "city." The path of the American urban structure has been analysed using different geographical units: counties (Beeson et al., 2001; Desmet and Rappaport, 2013), minor civil divisions (Michaels et al., 2012), metropolitan areas (Dobkins and Ioannides, 2000, 2001; Black and Henderson, 2003; Ioannides and Overman, 2003), urbanised areas (Garmestani et al., 2005) and the economic areas recently defined by Rozenfeld et al. (2011) using the city clustering algorithm. However, since our aim is to study the path of the urban system from its origin, we find it more appropriate to use data from "legal" cities, which are those reported since the first census in 1790.[4] Units such as metropolitan areas were introduced later.[5] Thus, we identify cities as what the US Census Bureau denominates incorporated places. These incorporated places have also been used recently in the empirical analyses of American city size distribution (Eeckhout, 2004, 2009; Levy, 2009; Giesen et al., 2010; González-Val, 2010).

The US Census Bureau uses the generic term "incorporated place" to refer to a type of governmental unit incorporated under state law, such as a city, town (except in New England states, New York and Wisconsin), borough (except in Alaska and New York) or village, with legally established limits, powers and functions. We take our data from the US Census Bureau (2004);[6] the sample consists of all the incorporated places with 100,000 inhabitants or more in 2000.[7]

Unincorporated places (concentrations of population that cannot be considered as part of an incorporated place but that are locally identified with a name) are excluded because they began to be counted after 1950 (they were renamed census designated places (CDPs) in 1980). Although some of them are consolidated as incorporated places and are reported in the 2000 census as cities, we also exclude them. The only exception is Honolulu CDP, because in Hawaiian state law there are no incorporated places.

Therefore, our final sample in 2000 consists of the 190 largest cities. This sample size is similar to that of other studies using metropolitan statistical areas (MSAs). Black and Henderson (2003) use data from 194 (1900) to 282 (1990) MSAs, while the sample of Ioannides and Overman (2003) ranges from 112 (1900) to 334 (1990). Their samples are slightly larger because in the US to qualify as an MSA a central city of 50,000 or more inhabitants is needed (a lower minimum population threshold than ours). In fact, most of these incorporated places are the central city of an MSA.

Table 1 shows the sample sizes for each decade and the descriptive statistics. The increase in the number of cities and the average growth rate of the cities by year are plotted in Figure 1, for the US and by region. For the first decades and until the mid-nineteenth century, the number of cities is low and grows very slowly; however, these few cities represent about two-thirds of the total urban population of the period. Many historians have documented the history of the US urban system (Hawley, 1981; Glaab and Brown, 1983; Chudacoff et al., 2010). Quoting Hawley (1981):

"At the conclusion of the Revolutionary War the westward movement of settlement began in earnest. Outposts had already been established at Detroit, Louisville, St. Louis, and New Orleans. With the accession of the Louisiana Territory, in 1803, these became rallying points for land-hungry settlers. New town sites soon appeared at Erie, Pittsburgh, Cincinnati, and elsewhere along the Ohio, Mississippi and Missouri Rivers. In every instance the new towns served as points of departure from which settlement fanned out over surrounding lands."

Several historical events (Hawley, 1981) facilitated the growth in the number of cities. These include the opening of the Erie Canal in 1825, which permitted a return flow of raw materials to Eastern centres from the West, the appearance of lake ports (Rochester, Toledo, Chicago or Milwaukee) and river ports (Pittsburgh, St. Louis, Cincinnati or Louisville) and the laying of railway lines across the mountains allowing access to Western raw materials and fostering Trans-Appalachian commerce at the time that new population centres were developed at division points along the routes (Columbus, Dayton, Indianapolis, Grand Rapids, Peoria, etc.).

From 1850 to 1900, the number of cities doubles (from 73 to 157). The last major entry of new cities takes place from 1900 to 1930, and from that date the number of cities remains stable. Figure 1 shows some regional differences: a marked increase in the number of cities in the West and South, while the number of cities in the Midwest and Northeastern regions remains stable. There is also a change in the average growth rates of the cities over time. Although growth rates decrease over time, growth in Western and Southern cities tends to be higher than the average after 1860. According to Hawley (1981):

"By 1860 the principal outlines of the urban pattern east of the Mississippi had been completed. All but a few of the present centers of 100,000 or more population in that section of the country had been founded. After the Civil War cities sprang up west of the Mississippi in rapid sequence along the newly completed transcontinental railways. Within a scant twenty years, by 1880, the urban network of the nation was virtually completed. The land ward drift of the population passed its peak in 1890. From that date to the present the prevailing trend in population redistribution has been cityward."

Finally, in 2000 the percentage of the urban population represented by this upper-tail distribution is much lower (31%) because of the appearance of many small and mid-sized cities (there were 19,296 incorporated places in the 2000 census, with an average population of 8,968.44 inhabitants) and because a change had taken place to a more stable and less concentrated city size distribution.

The relatively small size of our sample is not a problem for our methodology because the techniques we apply are especially designed for small samples. However, the sample is defined according to the largest cities in the latest period, which might imply a bias because these are the "winning" cities, namely those that have presented the highest growth rates over time. We deal with this potential problem in Sections 3 and 4.2 where this possible bias could have an influence, considering different sample sizes. Thus, although we have information on up to 190 cities, we always consider a lower sample size, namely the top 10, 75, 100 or 150 cities, defined according to years of reference different from the last period.

3. Testing long-term trends: random growth versus mean reversion

Description

Our basic hypothesis for long-term growth is random growth. Random growth theories are based on stochastic growth processes and probabilistic models. The traditional models are those of Champernowne (1953), Simon (1955) and more recently Gabaix (1999) and Córdoba (2008). When applied to population growth, these models are able to reproduce two empirical regularities that are well known in urban economics: Zipf's and Gibrat's laws (or the rank-size rule and the law of proportionate growth[8], respectively).

We follow the methodology proposed by Clark and Stabler (1991), who suggest that testing for random growth is equivalent to testing for the presence of a unit root. They build on the Vining model of city growth with autocorrelated errors (Vining, 1976). Let S_{it} be the size (population) of city i at time t. Starting from a simple autoregressive (AR) growth model, they assume that the relationship between the size of a city in time period t and $t-1$ is $S_{it} = \rho_{it} S_{it-1}$, where ρ_{it} is the growth rate of city i over the period $t-1$ to t. This growth rate can be decomposed into two (Clark and Stabler, 1991) or three components (Bosker et al., 2008): a random component, a non-stochastic component relating the current growth rate to a (possibly time-varying) constant and past growth rates, and initial city size. Then, after some algebra, Clark and Stabler (1991) get the following expression:

$$\Delta \ln S_{it} = c_i + \Theta_i \ln S_{it-1} + \sum_{j=1}^{n} \beta_{ij} \Delta \ln S_{it-j} + u_{it}, \qquad (1)$$

where c_i is a constant, β_{ij} is a parameter measuring the influence of past growth rates on current city growth and u_{it} is a random error term. Θ_i is the key parameter that captures the effect of initial city size on growth. Random growth would imply $\Theta_i = 0$, meaning that the growth of a particular city does not depend on the initial city size. This shows that testing for random growth (Gibrat's law) is equivalent to testing for a unit root in city sizes. Evidence supporting a unit root (if Θ_i is not significantly different from zero) means that city i's growth rate is independent of initial size. By contrast, when $\Theta_i < 0$ the path of city i will be a stationary process (mean reversion).[9] By using Eq. (1), Clark and Stabler (1991) apply the standard Dickey–Fuller (1979) t-statistic, failing to reject random growth for the seven largest cities in Canada from 1975 to 1984.

Results

Gabaix and Ioannides (2004) emphasise "*that the next generation of city evolution empirics could draw from the sophisticated econometric literature on unit roots.*" Following up on this suggestion, most of the recent studies apply unit root tests: Black and Henderson (2003), Sharma (2003), Resende (2004), Henderson and Wang (2007) and Bosker et al. (2008).

Some authors (Black and Henderson, 2003; Henderson and Wang, 2007; Soo, 2007) propose a growth equation to test the presence of a unit root, which they estimate by using panel data. However, there are problems with this methodology (Gabaix and Ioannides, 2004; Bosker et al., 2008; González-Val et al., 2014). First, data availability; our panel includes only 22 temporal observations as the periodicity of our data is by decades (decade-by-decade city sizes over a total period of 210 years), when the ideal would be to have at least annual data (see Clark and Stabler, 1991; Bosker et al., 2008). Most studies use data from the decennial census, so this limitation is a common problem in the literature. Second, an econometric issue; the presence of cross-sectional dependence across the cities in the panel can give rise to estimations that are not very robust. Cross-sectional dependence means that the cities are interdependent. The causes of cross-sectional dependence in the errors can be the presence of common shocks and unobserved components that ultimately become part of the error term, spatial dependence and idiosyncratic pair-wise dependence in the disturbances with no particular pattern of common components or spatial dependence. The econometric literature clearly establishes that panel unit root and stationarity tests that do not explicitly allow for this feature among individuals present size distortions that can lead to misleading inference (Banerjee et al., 2005).

For this reason, as in González-Val et al. (2014), we use one of the most recent tests especially created to deal with this question, namely Pesaran's (2007) test for unit roots in heterogeneous panels with cross-section dependence. The test of the unit root hypothesis is based on the t-ratio of the OLS estimate of b_i in the following cross-sectional augmented Dickey–Fuller (denoted by CADF) regression:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + e_{it}, \qquad (2)$$

where $y_{it} = \ln S_{it}$, a_i is the individual city-specific average growth rate and $\bar{y}_t$ is the cross-section mean of y_{it}, $\bar{y}_t = N^{-1}\sum_{j=1}^{N} y_{jt}$. To eliminate cross-dependence, standard Dickey–Fuller (or augmented Dickey–Fuller) regressions are augmented with the cross-section averages of lagged levels and first differences of the individual series, such that the influence of the unobservable common factor is asymptotically filtered. The null hypothesis assumes that all series are non-stationary, and Pesaran's CADF is consistent under the alternative that only a fraction of the series is stationary.

Another advantage of Pesaran's CADF test over other recently developed unit root tests (Levin et al., 2002) is that it is suitable for unbalanced panels, as is the case with our city sample.[10] New cities appear over time, from 16 in 1790 to 190 in 2000. However, owing to limitations in the data (the CADF test works with unbalanced panels but if we consider the complete sample it is a strongly unbalanced panel; there is an excessive amount of missing data because in the first period the population was only reported for 16 cities), we must restrict our analysis to a maximum of 150 cities. These 150 cities are a fixed sample for the entire period, and they correspond to the largest cities (upper-tail distribution) in the year of reference. We consider three periods: 1790–1900, 1900–2000 and 1790–2000. Obviously, the number of cities in each panel is fixed but some of the cities did not exist in all periods (in earlier periods there are a lot of missing data, which is why the panels of 1790–1900 and 1790–2000 are unbalanced). In the 1790–1900 period, the year of reference is 1860, while in 1900–2000 and 1790–2000, it is 1900 (we cannot always use the same year of reference owing to data limitations). In this way, we can control for the possible bias mentioned in Section 2, because not all the largest cities of 1860 or 1900 would have maintained their positions a century later. Therefore, the samples defined according to 1860 or 1900 ranks contain "winning" and "losing" cities.

Table 2 shows the results of the standardised Z t-bar statistic of the CADF test, $Z[\bar{t}]$, and the corresponding p-value for four sample groups (top 10, 75, 100 and 150 largest cities in the year of reference), different models, namely $AR(p)$ with $p = 1,2,3$ including a constant or constant and trend, and three different periods.[11] In Panel A

(1790–1900), we must restrict the analysis to the top 10 and top 75 cities owing to data limitations; the results show that we cannot reject the unit root in any case. Support for the unit root hypothesis is also strong in Panel B (1900–2000), as we can only reject the null hypothesis in one case: the model with one lag and no trend for the top 150 cities. Finally, Panel C, which considers the entire period 1790–2000, shows less conclusive evidence. In this panel, the results are similar for the four sample sizes. When only one lag is included, the null hypothesis of a unit root is rejected for any specification. However, as the number of lags in the model increases, we soon find evidence in favour of our null hypothesis: in the model with two lags when a trend is included and in the model with three lags with any specification. This last result is especially relevant, as Said and Dickey's (1984) $T^{1/3}$ rule would establish the lag choice $p = 3$ in that case $\left(22^{1/3} = 2.8\right)$.[12] This evidence in favour of a unit root indicates that overall city growth during the 1790–2000 period was independent of initial size, supporting our hypothesis of random growth. The evidence is even stronger when we consider the subperiods (1790–1900 and 1900–2000).[13]

4. What lies beneath random growth? Intra-distribution mobility

In Section 3, we found evidence supporting random growth against the alternative of mean reversion (convergence) in American cities from 1790 to 2000. In this section, we take a different perspective. Our intention is to examine mobility within the distribution in order to extract growth patterns different from the general unit root trend detected in the previous section. To do this, we use two techniques. First, we calculate transition matrices, which tell us the degree of mobility in terms of probability. Second, we apply a cluster algorithm to identify different groups of cities that converge with each other. Both approaches are complementary; while the transition matrices define some groups in relative terms and the movements of cities between these groups are examined, with the second method we use the algorithm to endogenously identify the groups of cities that converge over time, looking for evidence of some type of "local" mean-reverting behaviour.

4.1 Transition matrices

Description

Eaton and Eckstein (1997) were the first to apply Quah's (1993) transition matrices to study trends in city sizes. Let F_t be the vector representing the city size distribution at time t relative to the average size. We can say that this distribution follows a stochastic process defined by a Markov chain if the transition from one period to the next is given by

$$F_{t+1} = MF_t \tag{3}$$

where M is the movement matrix or transition matrix defining the law of movement from one period to the next, assuming we have a stationary process, and M is time-invariant. A Markov chain requires discrete time and a finite space of states E, which represents a discrete approximation to the population distribution. Implicit in (3) is also what is known as the Markov property, i.e., that the future of the process depends only on its most immediate past (a homogeneous first-order stationary Markov process). The element p_{ij} of the matrix M represents the probability that a city in state i in t moves to state j in $t+1$, $i, j \in E$. It is evident that $p_{ij} \geq 0$ and that $\sum_{j \in E} p_{ij} = 1, \forall i \in E$.

The elements of the matrix M can be estimated by maximum likelihood (Hamilton, 1994; Bosker et al., 2008), applying

$$\hat{p}_{ij} = \frac{\sum_{t=1}^{T-1} n_{it,jt+1}}{\sum_{t=1}^{T-1} n_{it}}, \tag{4}$$

where $n_{it,jt+1}$ is the number of cities moving from state i in year t to state j in year $t+1$ and n_{it} the number of cities in state i in year t.

The general expression (3) is valid for the case in which no cities enter or leave the sample from one year to the next. This is not our case, and thus we need to apply an extended equation, which describes the path of a distribution that allows cities to enter or leave.

In the case of a sample that grows over time, in which from one period to the next cities only enter and never leave the sample, Dobkins and Ioannides (2000) and Black and Henderson (2003) show that the correct equation is

$$F_{t+1} = (1 - i_t)MF_t + i_t Z_t \tag{5}$$

where i_t is a scalar denoting the percentage of new cities in $t+1$ over the total existing cities in $t+1$ and Z_t is the vector of relative frequencies of the cities that enter. It makes sense to consider only the possibility of entry, because in their samples once a metropolitan area reaches the minimum population threshold it never falls below it.

However, in our city (incorporated places) data, new cities can easily grow fast, surpassing other cities in size. Thus, there is a flow of new cities in the group of largest cities, while others drop down. In our case, where cities enter and leave the sample from one period to the next, Lanaspa et al. (2011) propose the next equation:

$$F_{t+1} = MF_t - n_t MX_t + n_t Z_t , \qquad (6)$$

where $n_t = \frac{N_t}{N}$ with N denoting the constant number of cities in each period and N_t representing the number of cities entering or leaving from t to $t+1$. Z_t (X_t) is the vector of the relative frequencies of the cities that enter (leave) the sample and M is the transition matrix from t to $t+1$ but only of the $N - N_t$ cities that are in the sample both in t and in $t+1$. The difference between Eq. (6) and Black and Henderson's (2003) expression (Eq. 5) is the term $n_t MX_t$, which represents the distribution of cities that leave the sample.

Results

Table 3 shows the M matrices for three periods (again 1790–1900, 1900–2000 and 1790–2000) and three sample sizes (75, 100 and 150 cities). This methodology always takes into account the largest cities at each moment in time, allowing these largest cities to change, enter or leave the sample, or remain in it from one period to the next.[14] Five states are considered; a larger number would increase mobility artificially and a smaller number would provide little information on intra-distribution mobility. The upper limits for each state are 0.4, 0.7, 1, 2 and ∞ times the average for each year.[15] The thresholds of the different categories are not exactly the same, but they are very similar to those used by Eaton and Eckstein (1997), Dobkins and Ioannides (2000) and Bosker et al. (2008). In any case, one of the criteria used to define them is that the number of cities in each of the categories should be equal. As is already known, the major problem with this approach is that any choice of states inevitably involves a certain amount of arbitrariness. We explored alternative cut-off points, although these are not very different from the states finally chosen, and the qualitative results remain the same. The relative frequencies are also shown of the cities that enter (Z_t) and leave the sample (X_t) throughout the period, as defined above.

Several conclusions emerge from Table 3. The first and most important is that we find intense mobility in the distribution of cities; persistence is not high. This is especially true for Panel A (1790–1900), which captures the creation of cities in the nineteenth century, and Panel C (1790–2000), which represents the aggregate period. In fact, many of the elements in the diagonal of the matrices in Panel A, which correspond to the cities that belong to the same state for two consecutive periods, are below 0.7, thus indicating high mobility in that period. Panel B shows less mobility, as most of the elements in the diagonal of the matrices are greater than 0.8. These results highlight the difference between the nineteenth (high mobility) and twentieth century (a more stable urban system). The matrices in Panel B are consistent with those of Black and Henderson (2003), as the period they consider is similar (1900–1990). Focusing on the aggregate period 1790–2000 (Panel C), of the fifteen elements in the diagonals, only three are higher than 0.9, while six values are between 0.7 and 0.8, and one is below 0.7. All of them are significantly different from one (the value one represents no transitions to any other states and thus absolute persistence).[16]

It is usual in the literature to find little mobility, as detected for the US by Black and Henderson (1999, 2003) and by Beeson et al. (2001), but those samples cover a considerably shorter time horizon than the one we consider. Our sample covers more than two centuries. By studying the urban structure from its beginning, the conclusions may be different because over these centuries, the late eighteenth, the nineteenth and the twentieth, the American urban structure was formed and built through demographic and territorial expansions.

The demographic expansion was related to waves of immigration throughout the nineteenth century. Immigrants from Britain continued to flow into American cities after independence. Furthermore, in addition to internal migration pressures because of changes in agricultural and industrial activities, rural people in Ireland, Germany and other parts of Europe suffered a severe blow from the mid-nineteenth-century potato blight. Chudacoff et al. (2010) provide impressive statistics and examples of the huge immigration received in the US:

"During the Great Famine of the late 1840s and early 1850s, 1.7 million Irish fled to the United States. (…) By the 1850s more than half residents of Boston and New York City were foreign born, and in Philadelphia 30 percent of household heads were born in Europe. (…) Southern cities in this era also received newcomers from abroad. By 1860, 40 percent of New Orleans's population was foreign born. (…) Between 1840 and 1890, 7.5 million Irish and German immigrants arrived in America. (…)

When the second wave began in the 1880s, more than 5.2 million immigrants arrived (…). Although large numbers of English, Irish, Germans, and Scandinavians continued to come, they were outnumbered by four new groups: Catholics from Eastern Europe, Catholics from Italy, Jews from Russia and Eastern Europe, and Catholics from Canada (…). Immigrants from both waves settled in cities, particularly in older, inner districts where they were close to job opportunities."

The territorial expansion was linked to the improving railway network. Manufacturing and commerce boosted urban growth, but railroads were essential to both commercial and industrial growth.[17] In the South, the expansion of the region's previously underdeveloped railroad system fostered wider commercial and industrial possibilities. Four transcontinental railroads pushed westward to the Pacific in the 1860s and 1870s, triggering urban growth along their routes (Chudacoff et al., 2010). These railroads helped complete the national urban network. Between 1860 and 1910, a long list of prominent new cities (nearly the entire urban West) were boosted by the railroads: Albuquerque, Dallas, El Paso, Fort Worth, Los Angeles, Minneapolis, Portland, Reno, Salt Lake City, San Antonio, San Diego, San Francisco, etc.

Other works that consider the same time horizon (1790–2000) also find evidence of high mobility within the distribution (Batty, 2006; Cuberes, 2011). Batty (2006) develops rank-clocks, where rank orders are plotted for each city in a temporal clockwise direction with the highest rank at the centre and the lowest on the circumference. Thus, he shows for the US, with the exception of New York, that the cities of the original 13 colonies gradually lost their positions through the entrance of new cities. Our data show the same behaviour as a consequence of the mobility noted above and the entry of new cities. If we rank the cities in 2000, only New York, Philadelphia, Boston and Baltimore of all the cities that existed in the first period (1790) are still among the top 20 cities (and only New York and Philadelphia remain in the top 10 cities), while the rest have lost their positions by being overtaken by other cities that entered the system later.

Cuberes (2011) finds that the average-rank of the fastest-growing cities (not just American cities, as his sample includes data for cities in other countries) tends to increase over time, a result that he interprets as evidence in favour of sequential urban growth. If cities grow sequentially, the cities that are initially the largest must represent a large share of the total urban population of the country in the initial periods and a relatively smaller one later on (although this is a necessary but not sufficient condition).[18] As Table 1 shows, the behaviour of our sample of cities is consistent with this affirmation.

The second conclusion refers to the cities that enter and leave the sample (Z_t and X_t measure the relative frequencies of the cities that enter and leave, respectively). In the three panels, those cities that leave the sample do so almost exclusively from the fifth state, that of the smallest cities. It makes sense that large cities do not disappear suddenly. The explanation given by Cuberes (2009) and Henderson and Venables (2009) is that there is irreversible investment; Glaeser and Gyourko (2005) argue that housing is a durable good that depreciates slowly over time. This fact is not the same for cities entering the sample; in Panels A and C, they enter in all the states, except for that of the largest cities. Nevertheless, in Panel B, which we claim represents a more stable urban structure, cities only enter the last two states (the smallest cities in the samples). From a long-term perspective (Panel C), this result indicates that cities enter the sample with a considerable size (most of them cities created in the West) and grow very quickly until they reach the sizes of pre-existing cities (leapfrogging).

4.2 Convergence clubs

Description

In the previous section, we find evidence of high mobility when we model growth as a first-order Markov process. That approach explains how cities move between the different population thresholds we defined; however, more or less movement does not automatically imply convergence or divergence. Therefore, in this section we apply a cluster algorithm to try to identify different groups of cities that converge with each other, looking for evidence of some type of “local” mean-reverting behaviour. Our convergence clubs are the groups of cities that converge in growth rates identified by the cluster procedure. Cluster analysis has previously been used to study clusters of cities within city size distribution (Garmestani et al., 2005), but here we look for clusters in city growth rates rather than clusters in city sizes.

The cluster procedure is based on the log $t-$test (Phillips and Sul, 2007, 2009), which focuses on the evolution over time of the idiosyncratic transitions in relation to the common growth component. Therefore, while in Section 3 we analysed the path of the common growth component by using panel unit root tests, we now focus on the possible differences in the idiosyncratic transitions across cities relative to the common growth component. This new approach is different from that of previous empirical studies of growth convergence clubs, such as the regression tree analysis used by Durlauf and Johnson (1995) and the predictive density of the data used by Canova (2004) to identify different clusters of countries or regions. The procedure by Phillips and Sul focuses on city growth relative to the average rather than on individual city growth. Thus, their methodology enables us to identify the relative transitions that occur within subgroups and to measure these transitions against the correlative of a common growth trend (Phillips and Sul, 2009). The regression model of the log $t-$test is

$$\log \frac{H_1}{H_t} - 2\log(\log t) = \beta_0 + \beta_1 \log t + u_t, \qquad \text{for } t = T_0, \ldots, T \tag{7}$$

where $\frac{H_1}{H_t}$ is the cross-sectional variance ratio, H_t is the transition distance, $H_t = N^{-1}\sum_{i=1}^{N}(h_{it}-1)^2$, and h_{it} is the relative transition coefficient, defined as $h_{it} = \frac{\log S_{it}}{N^{-1}\sum_{i=1}^{N}\log S_{it}}$ (again S_{it} is the size (population) of city i at time t.). These relative transition coefficients exclude the common growth component (μ_t) by scaling, measuring city i's transition element relative to the cross-section average. This means that h_{it} traces out city i's individual trajectory relative to the average, so Phillips and Sul (2009) call h_{it} the "relative transition path." Moreover, h_{it} also measures for each city i the departure from the common growth path μ_t in relative terms. Eq. (7) is obtained from a neoclassical growth model (see Phillips and Sul, 2007). Note that the hypothesis of random growth in the common growth component μ_t was tested in Section 3; thus, this cluster analysis is complementary to the unit root analysis performed previously. In Section 3, we tested random growth and the alternative was mean reversion for the entire sample, while here the cluster analysis focuses on local (or club) convergence relative to the overall growth component.

Thus, Eq. (7) simply represents a time series regression; the null hypothesis is growth convergence across all cities and the alternatives include no convergence and partial convergence among subgroups of cities. As the t-statistic of the test refers to the coefficient β_1 of the $\log t$ regressor in Eq. (7), the test is called the '$\log t$' convergence test. It is important that not only the sign of the coefficient β_1 of $\log t$ but also its magnitude measure the speed of convergence. The interpretation of the results may change depending on whether the estimated parameter is $0 \leq \beta_1 < 2$ or $\beta_1 \geq 2$. In the case that $\beta_1 \geq 2$ and the common growth component μ_t follows a random walk with drift or a trend stationary process,[19] then large values of β_1 will imply convergence in level city populations (cities end up with the same population). However, if $0 \leq \beta_1 < 2$, this speed of convergence corresponds to conditional convergence, in which population growth rates converge over time across the cities within the club.[20]

The cluster procedure performs the $\log t$ test for each of the groups and stops when the group of remaining cities does not satisfy the convergence test. First, it defines an initial core primary group, and other groups are then formed according to certain criteria that maximise the value of the t-statistic. A much more detailed explanation of the constructive steps of the procedure can be found in Phillips and Sul (2007, 2009).

Results

Table 4 shows the results of applying the cluster algorithm to our sample of cities.[21] We only consider the whole period (1790–2000); owing to data limitations, we cannot analyse subperiods as we did in the previous sections. Again, the results are reported for three sample sizes: the top 75, 100 and 150 largest cities in 1900.[22] In this case, the choice of the reference period is relevant, because the largest cities in 2000 are a sample of "winning" cities, those that since they first appeared have presented the highest growth rates.[23] However, some of the cities that were among the largest in 1900 have lost their positions in the ranking and have been overtaken by other cities. Therefore, if we consider this sample of cities, we capture more heterogeneous behaviours.[24]

The "club" column shows the number of cities that are members of each convergence group. The results are consistent for the three sample sizes, because despite enlarging the sample, the cities do not usually change groups. Only in the top 150 sample is there a small redistribution of cities, because one less convergence club is detected. The distribution of cities within groups can be found in the Appendix.

Given that the city distribution is fairly consistent regardless of the sample size, for clarity we show only the graphs for the top 75. Figure 2 shows the path over time of the log-population of the cities in each convergence club (we show the log-population because by definition the test is performed with log-variables). Our analysis focuses on these results. The first graph shows the path of the top 75 cities and demonstrates that it is difficult to infer any specific type of pattern. However, some of the groups represented in the remainder of the graphs show a sequential pattern, especially in the entry of new cities. These new cities appear later in the sample, but grow at a faster rate than do the rest of the cities in their club until they reach similar growth rates to the pre-existing cities.[25] It is remarkable that in almost all convergence clubs the cities do not appear in the sample at the same time, but rather sequentially. This behaviour is consistent with a pattern of sequential city growth, at least within groups, and is especially noticeable in the nineteenth century (when the entry of new cities is particularly intense), while in the twentieth century the city sizes are more stable in all groups (and the entry of new cities is much lower).

The algorithm classifies cities into 12 groups (convergence clubs). Four remaining cities are not classified into any club, and for these the convergence hypothesis is rejected. In each group, the estimated coefficient $\hat{\beta}_1$ is significantly positive, strongly supporting the club classification. Furthermore, only one of the estimated coefficients is significantly greater than two (club 2), indicating that the evidence in favour of level convergence is small, while support for conditional convergence within each of the other clubs is stronger because $\hat{\beta}_1 < 2$. Of the four cities belonging to club 2, three are in the South region, although the geographical distribution of cities shows no specific spatial pattern in any of the groups. Only club 11 consists of cities belonging to the same region (North-east), although another common characteristic of these cities is that they are among the oldest. The cities that have existed since 1790 are classified into groups 10 to 12, indicating that while they present a different growth pattern from the cities that appeared later, they also differ from each other.

It should be noted that of the 12 clubs, only clubs 1 and 2 correspond to cities that rise in the ranking (on average) from 1900 to 2000. The cities in the other clubs lose positions in the ranking (on average), especially those in clubs 7, 9 and 12, confirming our idea that our sample captures more heterogeneous behaviours than does the sample of "winning" cities in 2000, especially because we also include "failing" cities that performed poorly in terms of growth over the entire time interval. Furthermore, this result points to the presence of leapfrogging among cities in our sample, because some initially small cities are able to surpass some of the large ones in size.

5. Conclusion and discussion

In this paper, we study the growth pattern of the system of cities in the US during the 1790–2000 period. We find mixed evidence regarding city growth in the long-term. First, we cannot reject the random growth (unit root) hypothesis for most of the proposed specifications, against the alternative hypothesis of convergence (mean reversion), indicating that the growth rate does not depend on initial size. Previous studies also identify a random growth pattern (or Gibrat's law) for the case of the US, whether at the city level or with metropolitan areas, but focusing on shorter time periods (usually the twentieth century). Eeckhout (2004) considers the entire sample of places with no size restriction from 1990 to 2000 and finds evidence supporting random growth; González-Val (2010) generalises this analysis for all of the twentieth century, reaching the same conclusion from a long-term perspective. Ioannides and Overman (2003) use a metro areas database for the 1900–1990 period and cannot reject that growth was independent of city size, while for the same period Black and Henderson (2003) reject Gibrat's law for any sample section by using a different database of MSAs.

However, we also find evidence of high mobility when we model growth as a first-order Markov process. This mobility is consistent with the results of other studies that consider the same 1790–2000 period (Batty, 2006; Cuberes, 2011). Finally, by using a cluster procedure, we find strong evidence supporting conditional convergence in city growth rates within convergence clubs, which we can interpret as "local" mean-reverting behaviours. Other studies also find evidence of some degree of convergence when a time horizon longer than the twentieth century is considered. For example, Michaels et al. (2012) regress population growth on a full set of fixed effects for initial population density by using a dataset of minor civil divisions from 1880 to 2000, finding an increasing relationship between population growth and initial population density in intermediate densities. Beeson et al. (2001) use county-level census data from 1840 and 1990 and find evidence of population convergence only when the most heavily populated counties in 1840 are excluded from the sample. Therefore, the time period considered seems to be crucial. Kim (2000) and Kim and Margo (2004) explain that since the middle of the twentieth century, the pattern of urban development has differed in nature and scope from the industrial period because the overall pace of urbanisation has slowed and there has been a dispersal of the population out of central cities into suburban areas.

We interpret the high mobility and the results of the clustering analysis as signs of a sequential city growth pattern. Furthermore, both the transition matrices and the cluster analysis show that city sizes were more stable in the twentieth than in the nineteenth century, so sequential growth was mostly concentrated in the nineteenth century when many new cities appeared. However, are these different empirical results compatible? This question arises of whether a random growth result is compatible with a degree of convergence in the path of city growth rates. There is indeed a new mainstream in the literature that argues that random growth (or Gibrat's law) corresponds to the steady state, but that to reach that situation temporal episodes of different growth patterns across some cities are possible (including sequential city growth). Although the approach in these papers is different from ours because they track the behaviour of new cities since they enter the distribution by focusing on city age as a key variable, the general conclusion is similar, as they also find evidence of different growth patterns across cities (depending on city age) followed by an overall random growth pattern. Desmet and Rappaport (2013) use data from US counties and MSAs from 1800 to 2000 to conclude that in earlier periods smaller counties converge and larger ones diverge but both convergence and divergence dissipate and Gibrat's law gradually emerges. Sánchez-Vidal et al. (2014) obtain a similar conclusion by using un-truncated US incorporated places data, but considering only the twentieth century. They find that young small cities tend to grow at higher rates but, as the decades pass, their growth stabilises or even declines; after the first years of existence, Gibrat's law tends to hold better. Finally, Giesen and Südekum (2013) develop a theoretical model of urban growth with the entry of new cities, obtaining a pattern where Gibrat's law holds in the long run but where young cities (which tend to be relatively small) initially grow faster. This model is tested by using data on the exact foundation dates of 7,000 American cities for the period 1790 to 2000, confirming that the distribution of city sizes is systematically related to the country's city age distribution.

Our results are consistent with this literature and thereby lend support to recent theories of sequential city growth. Sequential growth theories should not be considered to be a rebuttal of the traditional theories; on the contrary, they provide a unifying framework including random growth (at the steady state) and temporal episodes of different growth patterns or mean reversion. However, these new theories open new interesting research issues. We need to know more about the factors driving the length of the transition to the steady state or the spatial dimension of this process, not explored in any study yet. Finally, it would be desirable to find empirical evidence from other countries. All of these questions deserve further research.

Endnotes

[1] We acknowledge one anonymous referee for suggesting this point.

[2] However, empirical studies demonstrate that in some cases their influence on determining agglomeration remains important; see Ellison and Glaeser (1999), Davis and Weinstein (2002) and Bleakley and Lin (2012).

[3] Many models in the literature explain spatial agglomeration in a dynamic context. Some of them can generate a growth pattern in the number of cities similar to sequential city growth, although they do not label it like that. For example, Henderson and Ioannides (1981) develop a theoretical framework in which cities are built at intervals that become shorter very rapidly.

[4] We talk about the "origin" of the urban system because the 1790 census was the first census that was published, and it provides data on the first 16 cities. However, these cities existed earlier. Kim (2000) provides data for four and five cities in 1690 and 1720, respectively. His data come from Bridenbaugh (1938) and the Historical Statistics of the United States. However, we prefer to use a single source of data, the US Census Bureau, to avoid differences between samples. In addition, the periodicity of these data would not be the same as the rest of the sample (decennial census).

[5] The standard definitions of metropolitan areas were first issued in 1949 by the then Bureau of the Budget, the predecessor of the present Office of Management and Budget.

[6] Source: Table 32. Only 16 of all the cities (8.42%) show a significant change in their boundaries (the case of annexed areas). Information about entities whose names and/or boundaries have changed, entities that no longer exist, newly established entities (both legal and statistical) and changes in geographic relationships is given in the "geographic change notes" section.

[7] Imposing a minimum population threshold is relevant for the analysis of city size distribution (Eeckhout, 2004). However, it seems to be less decisive in the study of city growth. González-Val (2010) obtains the same conclusion by using data from all incorporated places without any size restriction, as do Ioannides and Overman (2003) with their sample of MSAs: the validity of random growth in US city growth during the twentieth century. Cuberes (2011) carries out several robustness checks and his results for sequential city growth do not vary much with different cut-offs for selected cities.

[8] According to Gabaix and Ioannides (2004), *"Gibrat's Law states that the growth rate of an economic entity (firm, mutual fund, city) of size S has a distribution function with mean and variance that are independent of S."*

[9] A consequence of an estimated $\Theta_i < 0$ is that any shock will dissipate over time; see Davis and Weinstein (2002).

[10] Another panel test that deals with cross-section dependence and that is suitable for unbalanced panels is the Im et al. (2003) test (IPS test). We also calculated this test and the results lead to more rejections of the unit root null hypothesis than when using Pesaran (2007). However, we do not show these results because as Baltagi (2008, p. 280) points out, the IPS test has size distortions when, as in our sample, N is large relative to T. Another problem is highlighted by Breitung (2000), who finds that the IPS test suffers from a dramatic loss of power if individual specific trends are included.

[11] The estimations were carried out by using the pescadf Stata package, developed by Piotr Lewandowski. The number of elements (cities) in each panel in Table 2 is fixed but the number of observations by period can change (missing values because some of the cities did not exist in all periods). Thus, Panels A and C are unbalanced panels.

[12] Following the suggestion by Ng and Perron (1995), we also calculated the optimal number of lags for each individual city by using a 'general-to-specific procedure' based on the t-statistic. The average optimum number of lags is 2.5 for the top 75 cities, 2.4 for the top 10 and top 100 cities and 2.1 for the top 150.

[13] We carried out several robustness checks with the Panel C sample (the whole 1790–2000 period); the specific values of these tests are available from the authors on request. We defined the sample according to the largest cities in 2000, the latest period for which we have data, and the results are similar. We also tried to select the cities in the sample randomly and again we obtained the result that the null hypothesis

of a unit root could not be rejected. Finally, we estimated separately a panel for the sample of 16 cities that are present in all periods and the results for this group of the oldest cities are also similar.

[14] However, to define the largest cities in each period, entry and exit, we use all the cities available each year. Although our database is constructed by using an absolute cutoff (100,000 inhabitants or more in 2000), the minimum population needed to be within the largest 75, 100 and 150 cities in each period changes over time.

[15] The average is not calculated for all the cities, but for those that remain in the sample for two consecutive periods (see the definition of the matrix M).

[16] Standard errors, not shown, are available from the authors on request.

[17] Nevertheless, the effect on economic growth is not so clear. Fogel (1964) argues that the railway construction gave the American economy a boost, but of perhaps only a few percentage points of GDP.

[18] Cuberes (2011) explains that this pattern could also be consistent with non-sequential growth, providing the following example. Suppose that the initially largest city grows alone for a few years. After that, all cities grow at a rate equal to or higher than the first city. Therefore, the largest city would represent an increasing share of the total population in the initial years and this share would decline as the rest of the cities grow faster. Nevertheless, growth would not be sequential in the sense that the second city would not grow faster than the third one for a few decades, and so on.

[19] Note that the hypothesis of random growth in the common growth component was tested in Section 3.

[20] Note that this terminology is slightly different from the classical definition of conditional convergence, which depends on individuals' structural characteristics and initial conditions (Galor, 1996). An analysis of the general characteristics of the various convergence clubs as well as the many possible determining factors and initial conditions in each case is beyond the scope of this paper.

[21] The estimations were performed with the Gauss code kindly provided by Donggyu Sul on his webpage. As Phillips and Sul (2007) recommend, we set $r = 0.3$ (r is the initiating sample fraction).

[22] To apply the algorithm, we must have a balanced panel dataset. Given that most of the cities appear in the sample after 1790, we must carry out a little data transformation, assigning a population of 1 to the cities that did not exist in each period. This transformation means that these cities have a zero log-population in the periods in which they did not exist. If this change affected the cluster procedure, the cities that appear in the same period would be grouped in the same club; however, Figure 1 shows how the groups are formed by cities that appear in different periods.

[23] In fact, with the largest cities in 2000, we find only four convergence clubs, because all of them are cities characterised by high growth rates. The results are available from the authors on request.

[24]Altogether, 31 (20.7%) of the top 150 cities in 2000 are not in the top 150 cities in 1900. The differences are greater still in the top 75 and 100 cities, because there are 36 different cities (48% and 36% of the sample, respectively).

[25] Some of the graphs are similar to Figure 4 (a) in Henderson and Venables (2009), obtained from simulations of their theoretical model of city formation. However, these graphs should be taken with caution as they show log-population and the log-scale smoothes cross-city differences in levels. Moreover, because a city's log population is zero before it enters the sample, graphically most (but not all) of the catch-up is the steep segment for the single decade in which the city appears.

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Figure 1. Change in the number of cities and average growth rates, 1790–2000

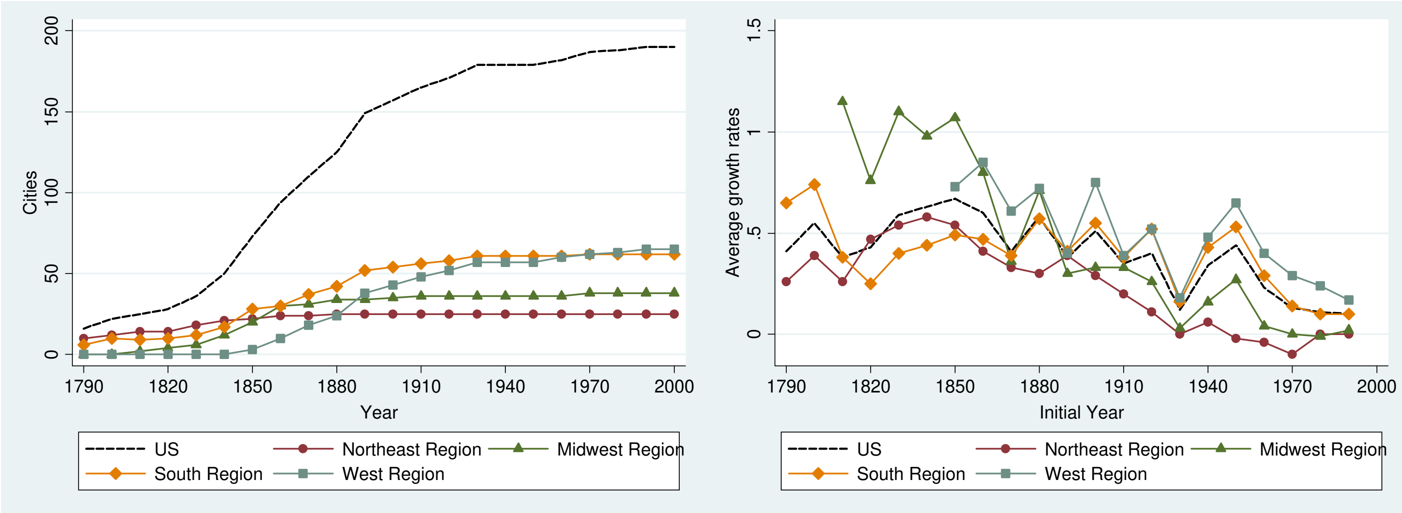
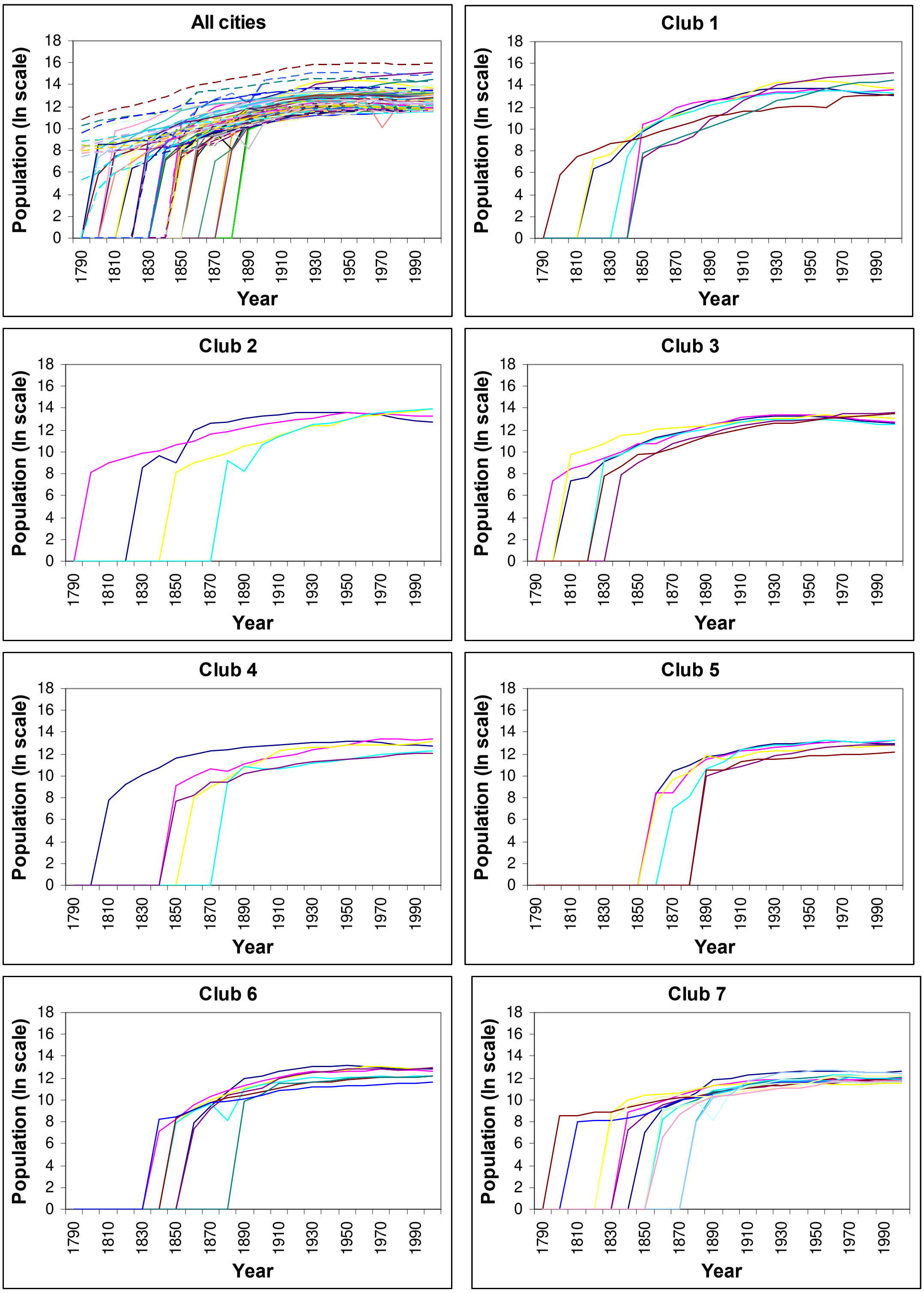
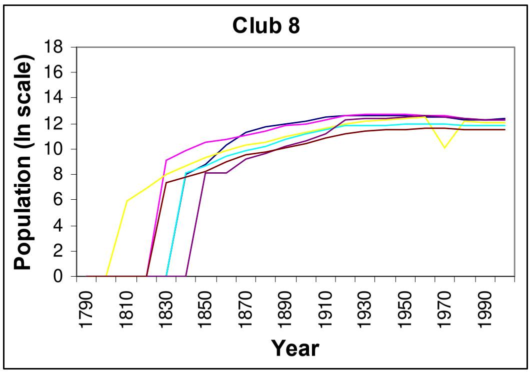
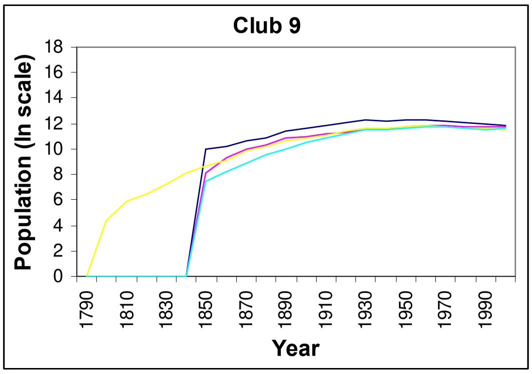
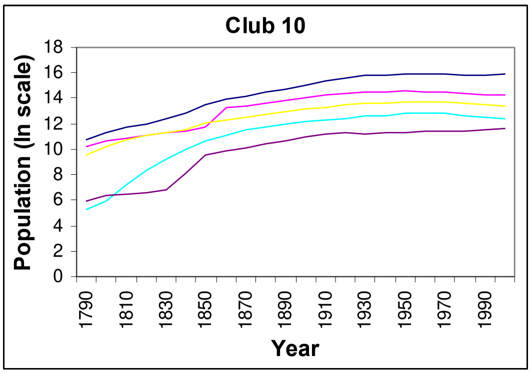


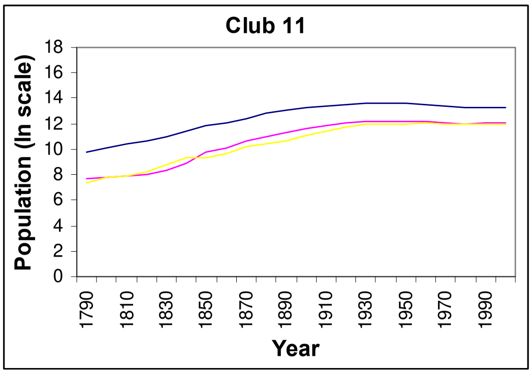
Figure 2. Cities' log population paths, Top 75, 1790–2000

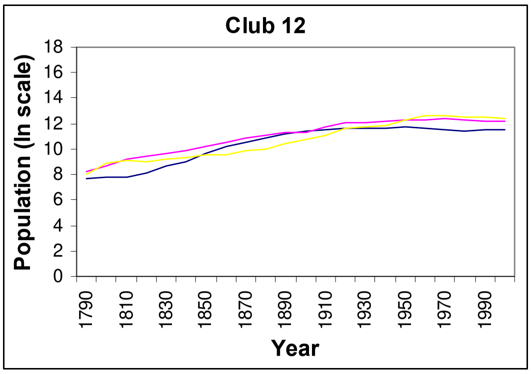












Note: Top 75 according to the ranks in 1900.

Table 1. Number of Cities and Descriptive Statistics by Year

Year	Cities	Mean	Standard deviation	Minimum	Maximum	US urban population (UP)	Percentage of UP in our sample
1790	16	8,746.50	13,313.13	200	49,401	201,655	69.40%
1800	22	10,255.00	18,565.84	81	79,216	322,371	69.98%
1810	25	14,278.04	26,052.55	383	119,734	525,459	67.93%
1820	28	16,832.07	31,499.38	606	152,056	693,255	67.98%
1830	36	20,631.19	43,079.73	877	242,278	1,127,247	65.89%
1840	50	24,502.46	58,753.40	1,222	391,114	1,845,055	66.40%
1850	73	30,220.67	85,663.40	415	696,115	3,574,496	61.72%
1860	94	44,193.24	136,697.40	175	1,174,779	6,216,518	66.82%
1870	110	55,417.75	160,729.66	155	1,478,103	9,902,361	61.56%
1880	125	65,037.17	197,482.93	556	1,911,698	14,129,735	57.54%
1890	149	77,799.07	232,080.75	273	2,507,414	22,106,265	52.44%
1900	157	108,432.39	329,863.51	202	3,437,202	30,214,832	56.34%
1910	165	142,935.56	433,335.63	297	4,766,883	42,064,001	56.07%
1920	171	176,340.04	509,938.16	326	5,620,048	54,253,282	55.58%
1930	179	211,572.36	614,701.55	515	6,930,446	69,160,599	54.76%
1940	179	224,762.88	651,013.99	582	7,454,995	74,705,338	53.85%
1950	179	260,994.59	695,986.21	727	7,891,957	96,846,817	48.24%
1960	182	290,794.10	683,649.24	3,695	7,781,984	125,268,750	42.25%
1970	187	308,875.27	679,828.20	14,089	7,895,563	149,646,617	38.60%
1980	188	311,706.85	617,176.35	62,134	7,071,639	167,050,992	35.08%
1990	190	332,701.32	635,704.55	95,802	7,322,564	187,053,487	33.79%
2000	190	364,890.56	690,433.95	100,565	8,008,278	222,360,539	31.18%

Note: US urban population data are taken from the US Census Bureau. Source: http://www.census.gov/population/censusdata/table-4.pdf.

Table 2. Panel unit root tests, Pesaran's CADF statistic

Panel A: 1790–1900. Year of reference for Top cities: 1860						
	Augmenting lag (1)		Augmenting lags (2)		Augmenting lags (3)	
Sample Size	Constant	Constant & trend	Constant	Constant & trend	Constant	Constant & trend
Top 10	4.448 (1.000)	4.522 (1.000)	10.877 (1.000)	8.882 (1.000)	10.877 (1.000)	8.882 (1.000)
Top 75	18.021 (1.000)	15.331 (1.000)				
Panel B: 1900–2000. Year of reference for Top cities: 1900						
	Augmenting lag (1)		Augmenting lags (2)		Augmenting lags (3)	
Sample Size	Constant	Constant & trend	Constant	Constant & trend	Constant	Constant & trend
Top 10	2.673 (0.996)	0.374 (0.646)	12.533 (1.000)	11.253 (1.000)	12.533 (1.000)	11.253 (1.000)
Top 75	5.152 (1.000)	1.049 (0.853)	34.011 (1.000)	30.349 (1.000)	34.011 (1.000)	30.349 (1.000)
Top 100	-0.799 (0.212)	2.250 (0.988)	39.273 (1.000)	35.044 (1.000)	39.273 (1.000)	35.044 (1.000)
Top 150	-5.100 (0.000)	2.612 (0.995)	48.540 (1.000)	43.583 (1.000)	48.540 (1.000)	43.583 (1.000)
Panel C: 1790–2000. Year of reference for Top cities: 1900						
	Augmenting lag (1)		Augmenting lags (2)		Augmenting lags (3)	
Sample Size	Constant	Constant & trend	Constant	Constant & trend	Constant	Constant & trend
Top 10	-4.110 (0.000)	-1.593 (0.056)	-1.394 (0.082)	-1.626 (0.052)	-3.212 (0.001)	-1.752 (0.040)
Top 75	-8.251 (0.000)	-8.067 (0.000)	-3.507 (0.000)	-0.805 (0.210)	4.165 (1.000)	12.598 (1.000)
Top 100	-5.489 (0.000)	-5.468 (0.000)	-0.071 (0.472)	1.575 (0.942)	10.535 (1.000)	18.987 (1.000)
Top 150	-7.645 (0.000)	-1.397 (0.081)	-2.471 (0.007)	9.946 (1.000)	20.622 (1.000)	28.679 (1.000)

Note: Pesaran's (2007) $Z\left[\bar{t}\right]$ test-statistic (p-value). Sample may not contain gaps; therefore, the eight gaps in the sample were filled using values calculated by linear interpolation.

Table 3. Average 10-year transition matrices

Panel A: 1790–1900

Sample Size: 75

	∞	2	1	0.7	0.4
∞	0.933	0.067	0	0	0
2	0.082	0.755	0.163	0	0
1	0	0.279	0.512	0.209	0
0.7	0	0.011	0.080	0.670	0.239
0.4	0	0.004	0.010	0.086	0.900
X_t	0	0	0	0	0.05751
Z_t	0	0.00160	0.00160	0.00320	0.14537

Sample Size: 100

	∞	2	1	0.7	0.4
∞	0.918	0.082	0	0	0
2	0.102	0.780	0.102	0.016	0
1	0	0.102	0.592	0.306	0
0.7	0	0.041	0.082	0.653	0.224
0.4	0	0.003	0.003	0.087	0.907
X_t	0	0	0	0	0.02307
Z_t	0	0.00136	0.00136	0.00407	0.13026

Sample Size: 150

	∞	2	1	0.7	0.4
∞	0.921	0.079	0	0	0
2	0.143	0.661	0.196	0	0
1	0	0.141	0.684	0.175	0
0.7	0	0.037	0.111	0.667	0.185
0.4	0	0	0.002	0.084	0.914
X_t	0	0	0	0	0.00407
Z_t	0	0.00114	0.00114	0.00457	0.14400

Panel B: 1900–2000

Sample Size: 75

	∞	2	1	0.7	0.4
∞	0.922	0.078	0	0	0
2	0.033	0.856	0.111	0	0
1	0	0.112	0.747	0.141	0
0.7	0	0.005	0.076	0.839	0.080
0.4	0	0	0.013	0.134	0.853
X_t	0	0	0	0.00135	0.07143
Z_t	0	0	0	0.00674	0.06604

Sample Size: 100

	∞	2	1	0.7	0.4
∞	0.913	0.087	0	0	0
2	0.056	0.839	0.105	0	0
1	0	0.118	0.756	0.126	0
0.7	0	0.009	0.101	0.780	0.110
0.4	0	0	0.011	0.122	0.867
X_t	0	0	0	0	0.06949
Z_t	0	0	0	0.00302	0.06647

Sample Size: 150

	∞	2	1	0.7	0.4
∞	0.898	0.102	0	0	0
2	0.068	0.837	0.095	0	0
1	0.006	0.116	0.749	0.129	0
0.7	0	0.018	0.078	0.806	0.098
0.4	0	0.002	0.003	0.125	0.870
X_t	0	0	0	0	0.03928
Z_t	0	0	0	0.00333	0.03595

Panel C: 1790–2000

Sample Size: 75

	∞	2	1	0.7	0.4
∞	0.928	0.072	0	0	0
2	0.050	0.820	0.130	0	0
1	0	0.162	0.676	0.162	0
0.7	0	0.006	0.077	0.792	0.125
0.4	0	0.002	0.012	0.106	0.880
X_t	0	0	0	0.00073	0.06506
Z_t	0	0.00073	0.00073	0.00512	0.10234

Sample Size: 100

	∞	2	1	0.7	0.4
∞	0.915	0.085	0	0	0
2	0.071	0.820	0.104	0.005	0
1	0	0.114	0.710	0.176	0
0.7	0	0.018	0.095	0.742	0.145
0.4	0	0.001	0.007	0.105	0.887
X_t	0	0	0	0	0.04971
Z_t	0	0.00058	0.00058	0.00347	0.09364

Sample Size: 150

	∞	2	1	0.7	0.4
∞	0.908	0.092	0	0	0
2	0.085	0.797	0.118	0	0
1	0.005	0.123	0.731	0.141	0
0.7	0	0.023	0.086	0.771	0.120
0.4	0	0.001	0.003	0.109	0.887
X_t	0	0	0	0	0.02608
Z_t	0	0.00042	0.00042	0.00379	0.07783

Table 4. Convergence clubs, 1790–2000

Club	$\hat{\beta}_1$ (t-statistic)	Club	$\hat{\beta}_1$ (t-statistic)	Club	$\hat{\beta}_1$ (t-statistic)
1 [7]	0.105 (0.146)	1 [12]	0.744 (2.386)	1 [26]	1.217 (6.979)
2 [4]	2.507 (3.844)	2 [7]	0.671 (4.686)	2 [17]	0.254 (3.720)
3 [6]	0.893 (2.326)	3 [6]	0.893 (2.326)	3 [9]	0.225 (2.674)
4 [5]	0.256 (3.225)	4 [7]	0.142 (0.910)	4 [15]	0.141 (1.634)
5 [6]	0.294 (1.885)	5 [12]	0.560 (2.119)	5 [20]	0.400 (1.462)
6 [8]	0.435 (5.784)	6 [12]	0.010 (0.087)	6 [23]	0.064 (0.502)
7 [14]	0.224 (2.389)	7 [18]	0.370 (4.367)	7 [21]	0.539 (4.215)
8 [6]	1.970 (1.188)	8 [6]	1.970 (1.188)	8 [3]	2.405 (2.303)
9 [4]	0.353 (0.985)	9 [5]	0.700 (2.794)	9 [6]	0.011 (0.396)
10 [5]	0.224 (4.673)	10 [5]	0.224 (4.673)	10 [3]	0.842 (6.385)
11 [3]	0.842 (6.385)	11 [3]	0.842 (6.385)	11 [3]	0.347 (0.711)
12 [3]	0.347 (0.711)	12 [3]	0.347 (0.711)		
Sample Size: Top 75		Sample Size: Top 100		Sample Size: Top 150	

Notes: The numbers in brackets are the number of cities. Top cities are defined according to the ranks in 1900. The corresponding t-statistic in the regression is constructed in the usual way by using HAC standard errors. At the 5% level, the null hypothesis of convergence is rejected if the t-statistic < -1.65. All the t-statistics reported are positive, indicating that we cannot reject the null hypothesis at 5% in any case.

Appendix: Cities within clubs

Rank in 1900	First year in the sample	Name (State)	Club (Sample Size: Top 75)	Club (Sample Size: Top 100)	Club (Sample Size: Top 150)
1	1790	New York (NY)	10	10	9
2	1840	Chicago (IL)			
3	1790	Philadelphia (PA)	10	10	9
4	1830	St. Louis (MO)	2	2	2
5	1790	Boston (MA)	11	11	10
6	1790	Baltimore (MD)	10	10	9
7	1820	Cleveland (OH)	1	1	1
8	1810	Buffalo (NY)	3	3	3
9	1850	San Francisco (CA)	1	1	1
10	1810	Cincinnati (OH)	4	4	4
11	1800	Pittsburgh (PA)	3	3	3
12	1810	New Orleans (LA)	3	3	3
13	1820	Detroit (MI)	1	1	1
14	1840	Milwaukee (WI)	1	1	1
15	1800	Washington (DC)	2	2	2
16	1830	Newark (NJ)	3	3	3
17	1840	Jersey City (NJ)	8	8	7
18	1790	Louisville (KY)	10	10	9
19	1860	Minneapolis (MN)	6	6	6
20	1790	Providence (RI)			
21	1840	Indianapolis (IN)	3	3	3
22	1860	Kansas City (MO)	5	5	5
23	1850	St. Paul (MN)	7	7	6
24	1830	Rochester (NY)	8	8	7
25	1860	Denver (CO)	5	5	5
26	1840	Toledo (OH)	6	6	6
27	1830	Columbus (OH)	3	3	3
28	1790	Worcester (MA)	11	11	10
29	1850	Syracuse (NY)	9	9	7
30	1790	New Haven (CT)			
31	1840	Paterson (NJ)	7	7	7
32	1860	Omaha (NE)	5	5	5
33	1850	Los Angeles (CA)	1	1	1
34	1850	Memphis (TN)	4	4	4
35	1830	Lowell (MA)	7	7	7
36	1790	Cambridge (MA)	12	12	11
37	1860	Portland (OR)	4	4	4
38	1850	Atlanta (GA)	6	6	6
39	1850	Grand Rapids (MI)	6	6	6
40	1810	Dayton (OH)	8	8	6
41	1790	Richmond (VA)	12	12	11
42	1800	Nashville-Davidson (TN)	1	1	1
43	1870	Seattle (WA)	5	5	5

44	1790	Hartford (CT)			
45	1840	Bridgeport (CT)	8	8	7
46	1860	Oakland (CA)	6	6	6
47	1860	Des Moines (IA)	7	7	7
48	1790	Springfield (MA)	11	11	10
49	1850	Evansville (IN)	9	9	7
50	1790	Manchester (NH)	10	10	9
51	1840	Peoria (IL)	7	7	7
52	1800	Savannah (GA)	7	7	7
53	1860	Salt Lake (UT)	7	7	7
54	1850	San Antonio (TX)	2	2	2
55	1800	Erie (PA)	9	9	8
56	1810	Elizabeth (NJ)	7	7	7
57	1880	Kansas City (KS)	7	7	6
58	1860	Yonkers (NY)	7	7	6
59	1790	Norfolk (VA)	12	12	11
60	1860	Waterbury (CT)	7	7	7
61	1850	Fort Wayne (IN)	6	6	6
62	1850	Houston (TX)	1	1	1
63	1850	Akron (OH)	8	8	7
64	1880	Dallas (TX)	2	2	2
65	1880	Lincoln (NE)	4	4	4
66	1890	Honolulu CDP (HI)	5	5	5
67	1830	Mobile (AL)	7	7	6
68	1880	Birmingham (AL)	7	7	7
69	1850	Little Rock (AR)	4	4	4
70	1890	Tacoma (WA)	5	5	5
71	1890	Spokane (WA)	6	6	6
72	1850	South Bend (IN)	9	9	8
73	1830	Allentown (PA)	8	8	7
74	1840	Springfield (IL)	6	6	6
75	1860	Topeka (KS)	7	7	7
76	1850	Knoxville (TN)		5	5
77	1860	Rockford (IL)		7	6
78	1840	Montgomery (AL)		4	4
79	1870	Chattanooga (TN)		6	6
80	1850	Sacramento (CA)		2	2
81	1850	Jacksonville (FL)		1	1
82	1880	Fort Worth (TX)		4	4
83	1860	Cedar Rapids (IA)		6	6
84	1790	Lexington-Fayette (KY)		6	6
85	1880	Wichita (KS)		5	5
86	1850	Springfield (MO)		5	5
87	1850	Austin (TX)		1	1
88	1870	San Jose (CA)		1	1
89	1880	Colorado Springs (CO)		1	1

90	1870	Waco (TX)	7	6
91	1890	Newport News (VA)	5	5
92	1850	Madison (WI)	5	5
93	1850	Charlotte (NC)	2	2
94	1860	San Diego (CA)	1	1
95	1840	Columbus (GA)	5	5
96	1860	Stockton (CA)	2	2
97	1840	Portsmouth (VA)	9	7
98	1860	Lansing (MI)	7	7
99	1850	Shreveport (LA)	6	6
100	1880	Stamford (CT)	7	6
101	1880	El Paso (TX)		2
102	1870	Tampa (FL)		6
103	1790	Alexandria (VA)		9
104	1860	Ann Arbor (MI)		5
105	1870	Winston-Salem (NC)		5
106	1800	Raleigh (NC)		2
107	1860	Laredo (TX)		2
108	1890	Berkeley (CA)		7
109	1860	Flint (MI)		8
110	1880	Fresno (CA)		1
111	1840	Baton Rouge (LA)		4
112	1890	Oklahoma City (OK)		4
113	1870	Greensboro (NC)		4
114	1890	Beaumont (TX)		7
115	1890	Pasadena (CA)		6
116	1850	Huntsville (AL)		3
117	1890	Riverside (CA)		1
118	1880	Vallejo (CA)		4
119	1850	Jackson (MS)		5
120	1870	Tucson (AZ)		2
121	1860	Independence (MO)		5
122	1880	Durham (NC)		2
123	1860	Santa Rosa (CA)		1
124	1890	Albuquerque (NM)		2
125	1880	San Bernardino (CA)		3
126	1870	Boise (ID)		1
127	1890	Phoenix (AZ)		1
128	1890	Pomona (CA)		3
129	1890	Santa Ana (CA)		1
130	1890	Bakersfield (CA)		1
131	1860	Corpus Christi (TX)		4
132	1870	Reno (NV)		1
133	1870	Salem (OR)		2
134	1890	Abilene (TX)		6
135	1890	Salinas (CA)		1

136	1870	Eugene (OR)	2
137	1840	Tallahassee (FL)	2
138	1890	Hampton (VA)	5
139	1890	Orlando (FL)	2
140	1890	Long Beach (CA)	4
141	1890	Modesto (CA)	1
142	1870	Hayward (CA)	4
143	1900	Miami (FL)	5
144	1890	St. Petersburg (FL)	5
145	1870	Anaheim (CA)	1
146	1890	Amarillo (TX)	5
147	1900	Tulsa (OK)	4
148	1870	Plano (TX)	1
149	1880	Orange (CA)	1
150	1890	Arlington (TX)	1