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Understanding Recent Growth Dynamics in Small Urban Places: The Case of New England

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This article utilizes recently published US Census data covering the pre-and post-Great Recession period (1990–2015) to identify key determinants of growth among small urban places in the New England Region. We find little evidence of random growth and robust evidence of convergence in growth, indicating that smaller urban areas tend to experience faster rates of growth than larger ones, over both the short and long term. Factors such as distance to large city areas and amenities are found to be particularly relevant to population growth rates. Having a diverse industrial base, high levels of human capital and proximity to large urban areas are factors that positively affect income growth. These results highlight the importance of policies geared to improve cities' amenities, increase their industrial diversity, and attracting and retaining human capital in urban areas.

INTRODUCTION

Habitat III, the United Nations Conference on Housing and Sustainable Development, strongly advocated for the need for a "New Urban Agenda" to make cities sustainable, inclusive and resilient. Key to the strategy is the role of Small and Mid-Sized Cities (SMCs, henceforth), in achieving key development priorities, such as affordable, resilient and safe housing, with infrastructure and services, which can facilitate effective trade, alleviate poverty and link communities to local, subnational, national, regional and global markets.[1]

Many SMCs can be characterized as having a very narrow and specialized productive base, with low connectivity and high rates of outmigration. These urban locations also frequently face physical, financial and human resource skill constraints (Cox and Longlands 2016). Collectively, these factors can significantly hamper prospects for achieving long-term sustainable growth. Additionally, having a narrow production base and limited resources also make such cities more volatile and susceptible to exogenous shocks. In the case of the United States, SMCs in the Mid-West and Northeastern regions have been particularly impacted by negative economic shocks as well as the decline and eventual

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deindustrialization of traditional industries such as textiles, steel production, mining, paper manufacture, railroad, and shipping (Bluestone and Harrison 1982; Bryce 1977).

This article seeks to uncover key determinants of growth among SMCs in the New England region. We leverage a major global economic shock, the Great Recession of 2007–2009, to identify the determinants for growth over three key periods; 1990–2010, which ends one year after the Great Recession; 2010–2015 or the post Great Recession period; and finally, over the full sample period, 1990 –2015. By focusing on three distinct periods, we hope to uncover key drivers of growth and resilience among small urban places in this region. The study of the New England region is particularly interesting because of its rich history in traditional manufacturing industries, such as textiles, paper making, machine tools, and industrial equipment (Temin 1999). The region has been very vulnerable to the relatively recent structural changes in the U.S. economy, most notably the extraordinary growth of the service sector, and the Great Recession of 2007–2009. The latter has forced profound changes in the industrial base, with accompanying changes in income levels, housing prices, poverty levels, and migration patterns across the region. Additionally, most urban places in the New England region (with the exception of Boston) can be classified as small and mid-sized urban areas.[2] In this regard, the New England region offers a rich opportunity to understand growth dynamics among SMCs communities, both over the short and longer term. It is important to mention that the article analyzes only the New England states of Massachusetts, Rhode Island, and Connecticut which are currently part of the Federal Reserve Bank of Boston "Working Cities" challenge, a program focused on the regeneration of growth among small and mid-sized cities in the New England region.[3]

We use data on both population and income growth to study the evolution of the New England SMCs. In the spirit of Glaeser et al. (1995) and González-Val (2015), we argue that, while population and income growth at the city level often go hand in hand, studying both variables separately is important to understand the evolution of these locations. Implicit in this approach is that growing cities will, over time, attract new residents and also achieve increases in productivity levels, frequently measured in terms of real per capita income.

As a first step, we test for random growth or Gibrat's Law of proportional growth, which predicts that cities' population growth to be independent of their size. Next, we test for conditional convergence in growth among small urban communities during the postrecovery (2010–2015) period and over the longer term (1990–2010 and 2015). Conditioning on a large set of factors that have been shown to be important for city growth allows us to uncover the key factors behind the growth performance of our sample of cities.

Results of parametric and nonparametric tests lead us to reject Gibrat's Law of proportional growth: our estimates point to high variability in population growth among smaller relative to larger urban locations, particularly over the longer term. Formal tests for conditional convergence confirm convergence in population and income growth over the longer term and convergence in income growth during the postrecovery period. The latter result suggests the relative sluggishness of population growth levels to adjust over the short-term postrecovery period. Rising unemployment rates are negatively related to population growth, reflecting the tendency of workers to relocate from high to low unemployment regions. Somewhat surprisingly, proximity to coastal areas, and to regional airports are associated with lower levels of population growth.

In terms of the determinants of income convergence, factors such as proximity to a major central city center (in our case New York City and Boston) and higher long-term summer temperature levels, are found to be associated with real income growth over both the long-term and also in the short-term postrecovery period. We also find a significant impact of human capital on city's income growth. Our estimates indicate that a 10 percent increase in the percentage of college-educated population is associated with an increase in real per capita income of 4 percent. Industrial diversity is also a common factor that spurs income growth: a 10 percent increase in the levels of industrial diversity increased productivity levels by as much as 5 percent over the long term. These results highlight the importance of locational factors such as temperature and proximity to major urban centers, but also policy factors such as the ability to attract and retain high-quality human capital, as well as having a diverse industrial base to build resiliency and sustain growth among SMCs.

The remainder of the article is organized as follows. "Background: Decline in Manufacturing and Changing Prosperity in the New England Region" section highlights recent trends in manufacturing growth and decline among cities in the New England region. "Related Literature" section provides a brief overview of theories and empirical papers on city growth. Our data is discussed in "Data" section, and an outline of the methodology used and the empirical models estimated are provided in "Methodological Approach" section. Our results are presented in "Results" section. Finally, concluding remarks are provided in "Conclusions" section.

BACKGROUND: DECLINE IN MANUFACTURING AND CHANGING PROSPERITY IN THE NEW ENGLAND REGION

Historically, the Northeast region of the United States benefited from the early shift from agricultural production to growth in textile and light manufacturing industries. The technology and the know-how for many of these industries were imported from European production centers and adapted to the local conditions, taking advantage of the presence of many water bodies that were used to power them (Temin 1999). Increasing innovation, specialization, and standardization coupled with the availability of an abundant literate workforce resulted in increased productivity and competitiveness during the early industrial period (Steinberg 2003; Temin 1999). Throughout the early 20th-century growth in industries stimulated increases in employment, wages, and housing prices in this region up until around the late 1960s (Yoon 2013). Population levels continued to grow both in the larger production centers but also spread to the smaller and mid-sized urban communities.

Starting in the 1970s and through to the 1990s, employment in traditional manufacturing throughout the United States began to decline. The Midwestern and the New England regions, later known as the "Rust Belt," were severely hit by this decline. Figure 1 displays this downward trend in employment in manufacturing for the New England region relative to the rest of the United States. The weakening in the manufacturing sector was the consequence of, among other factors, increasing competition from lower-cost producers from abroad, as well as a decline in local productivity (Blanchard et al. 1992; Yoon 2013). The economic decline experienced during this period was accompanied by the transitioning of the population from the Midwest and Northeastern regions' "Rust

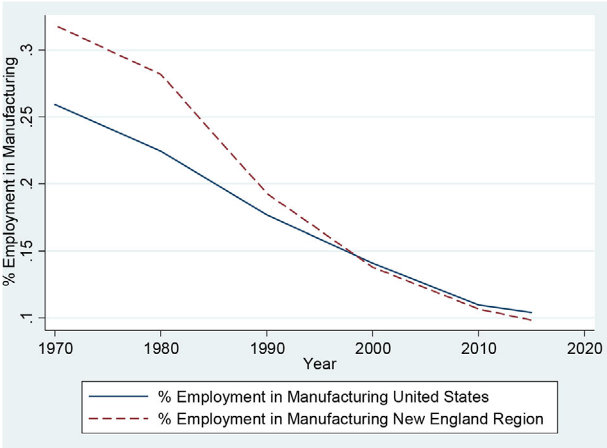

FIG. 1. Percentage employment in manufacturing 1970–2015.
(*Source:* ACS from the IPUMS 1970–2015)
[Color figure can be viewed at wileyonlinelibrary.com]
Notes: Figure 1 outlines percentage employment in manufacturing for the United States and the New England region over the period 1970–2015.

Belt" to the West and South "Sun Belt" regions of the United States. This was facilitated by a reduction in transportation costs, as well as the widespread use of air-conditioning, which facilitated an inflow of population in the warmer South and Western United States (Rappaport 2007).

Apart from this long-term decline in manufacturing, the major shock caused by the Great Recession of 2007–2009 had a distinctive impact on the New England region. The Great Recession, which was initially triggered by the collapse in the U.S. housing market, had a devastating impact on the entire U.S. economy. Nationwide job losses are estimated to have averaged 712,000 per month between October 2008 and March 2009 (Goodman and Mance 2011). The resulting slump in aggregate demand spread throughout the United States and forced many already struggling U.S.-based manufacturing companies to eventually close or shift operations abroad (Baily and Bosworth 2014). Between 2000 and 2010, over 141,000 manufacturing jobs had been lost in the New England region.[4]

As such, the fallout in terms of rising poverty levels and social displacement has been significant within this region, with substantial spatial variation in poverty levels. In some urban locations, poverty levels increased by as much as 13 percent between 2010 and 2015 with more than 34 percent of the population relying on the state Supplementary Nutrition Assistance Program (SNAP) to support their basic dietary needs in the same year.[5]

Figure 2 also traces the dynamics of population and income growth over the period 1980–2015. Prior to 1990, growth in both population and income appeared to be buoyant in the New England region. However, between 1990 and early 2000, we note a significant reduction in growth rates, particularly in the case of real per capita income, which appears to stagnate during the Great Recession period, and up to the end of 2015. On the other hand, population growth, while slowing over the period 2000–2010, does appear to recover during the post-Great Recession period 2010–2015.

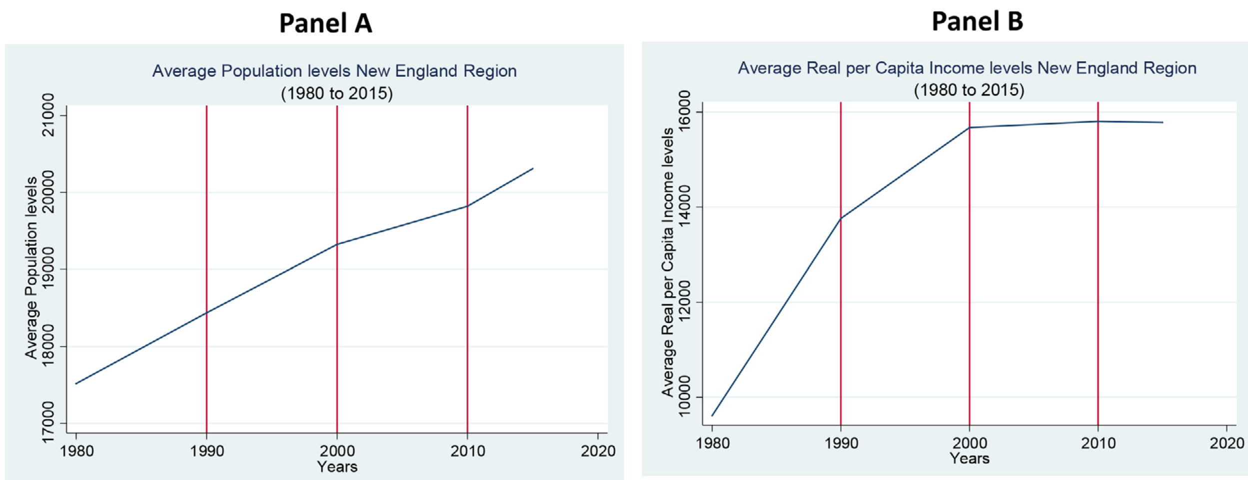

FIG. 2. Change in population and real income in the New England region, over the period 1980–2015.
(*Source:* ACS from the IPUMS 1980–2015)
[Color figure can be viewed at wileyonlinelibrary.com]

Notes: Figure 2 outlines changes in average population and real income in the New England region over the period 1980–2015. Panel A outlines changes in population levels, while Panel B outlines changes in real per capita income.

For our analysis, we divide the 1990–2015 time interval into two periods: the pre-Great Recession one (1990–2010) and the post-Great Recession one (2010–2015). In some regressions, we also analyze the evolution of income and population over the entire period (1990–2015) to shed light on the long-run trends of the New England economy.

RELATED LITERATURE

The existing literature on the growth of cities is too vast to be summarized here.[6] City growth has been commonly measured in terms of the growth of its population. The analysis based on growth in income per capita at the city level is much more scant, mostly due to a lack of reliable data. However, it is generally accepted that both measures are largely interconnected and tend to move in the same direction over time (Da Mata et al. 2005; González-Val 2015). In this section, we will focus on reviewing a few relevant papers that consider the U.S economy only. Our main takeaway from these studies is that most of them consider either all cities or only the largest ones and do not treat SMCs as urban centers that may have different characteristics than the largest ones.

POPULATION GROWTH AT THE CITY LEVEL

Our reading of the literature on city population growth is that it can be roughly divided into two groups of papers: those that study Gibrat and Zipf's Laws and those that analyze the key determinants of city growth.[7] Within the first group, Gibrat's Law, also known as the law of proportional growth, hypothesizes that growth among cities follows a stochastic process, frequently modeled to stem from exogenous productivity shocks. A key prediction of Gibrat's Law is a common mean and variance of growth rates across cities, which implies growth among cities to be independent of city size. This regularity, although often accepted as a good approximation to the data, is rejected depending on the time frame and the sample of cities used (Black and Henderson 1999; Desmet and Rappaport 2017; González-Val et at. 2014; González-Val 2010; Levy 2009).

Gibrat's Law implies (see Gabaix, 1999) that the city size distribution is well approximated by a Pareto distribution with a parameter nearing the value of one, a phenomenon that has been labeled as Zipf's Law.[8] This law is usually accepted as a robust regularity (Eeckhout 2004; Gabaix 1999; González-Val et al. 2014; Ioannides and Overman 2003; Ioannides and Skouras 2009; Nitsch 2005; Soo 2005; Soo 2014).[9]

A second branch of the literature seeks to identify specific determinants of population or employment city growth. Some important papers that have estimated these types of regressions in the United States are Glaeser et al. (1992), Glaeser et al. (1995) and Black and Henderson (1999). Factors such as road and rail density, availability of amenities, human capital, the percentage of small firms and the degree of industrial diversity have been found to be conducive to population growth, particularly among larger urban centers. However, there remains limited research in terms of which of these factors are particularly relevant for smaller urban locations. The abundance of small and medium cities together with the rich history of manufacturing in the New England area allows us to assess the impact of prior specialization in manufacturing on current growth patterns in these types of cities. The issue stems from the problem of "legacy" cities, which are former industrial cities and towns which have been negatively impacted by structural changes in the local economy. These changes forced the closure of key industrial companies, eventually leading to massive out-migration and stunted productivity growth (Mallach 2010; Mallach and Brachman 2013). Many of these cities and towns have struggled to recover and continue to be at a disadvantage in terms of achieving long-term sustainable growth and development. This article helps assess to what extent early specialization in manufacturing can hamper long-term growth, a term we label the "legacy effect."

GROWTH IN INCOME AT THE CITY LEVEL

Decades after the seminal paper by Solow (1956) the study of beta-convergence or regression to the mean in per capita income across countries proliferated (Barro 1991; Barro and Sala-i-Martin 1992; Barro and Sala-i-Martin 1991; Mankiw et al. 1992).[10] Some papers also focused on convergence within countries (Dobson et al. 2006), although they typically study convergence between regions, not between cities or metropolitan areas (MAs), in large part due to the difficulties associated with having accurate data at the city or MA level. However, focusing on cities to understand income convergence is, as argued in Glaeser et al. (1995), important since inputs are more mobile across cities than across larger geographies. Moreover, ideas are shared more easily in cities and their diffusion is known to be a crucial engine of growth (Lucas 1988; Romer 1986). Finally, Glaeser and coauthors argue that institutions being also a vital growth determinant at the country level (Acemoglu et al. 2009; Barro and Sala-i-Martin 1991) are likely to also determine growth at a more disaggregated level. Studying whether this is also true in the case of cities is relevant, especially given the fact that they often have a large degree of autonomy to govern themselves. Henderson and Wang (2007) show a positive relationship between a country's political institutions and its urbanization rate, but they do not use city-level data to test this.[11]

Our growth regressions closely follow those of Glaeser et al. (1995) who study the determinants of population and income growth in the United States between 1960 and 1990. A major difference between their study and ours is that they only analyze the largest 203 cities, whereas we focus on SMCs. They find that population and income at the city level tend to move together. Both variables are positively related to initial schooling and negatively related to initial unemployment and the initial share of employment in manufacturing. In an updated version of that paper, Glaeser and Shapiro (2003) show that the 1990s were an unusually good decade for the largest American cities, in particular for the cities in the Midwest. One of their key results is that the main determinants of city growth (human capital, good weather, and being a city built around the automobile industry) have not changed much relative to those of 1960–1990.[12] In a similar paper, Crihfield and Panggabean (1995) study conditional convergence in income among U.S. cities estimating growth convergence models similar to those used in Barro and Sala-i-Martin (1991). They use data for 282 metropolitan areas for the period 1960–1982 and conclude that there is substantial convergence between poor and rich cities. Finally, using a different empirical strategy, Drennan and Lobo (1999) confirm the existence of income convergence in U.S. cities for the period 1969–1995 using a test for the income-convergence hypothesis that is robust to the so-called "Galton's fallacy" critique of growth convergence regressions.

GROWTH DYNAMICS AMONG SMCs

Although most of the literature on city growth in the United States has focused on growth dynamics among the largest cities, a few studies have studied SMCs. Bryce (1977), first highlighted the unique challenges faced by SMCs such as limited revenue sources, scarce management capabilities, diseconomies in service availability, a very narrow and at times specialized productive base, and the tendency for large city biases in terms of being selected for federal grants-in-aid programs. Henderson (1997) emphasized the need for an examination of mid-sized cities given the proliferation and the growing importance of such cities in many emerging and developed economies. More recently, Cox and Longlands (2016) added that many SMCs generally have high rates of out-migration, a very narrow productive base, limited connectivity, and important resource constraints, all of which are can be a hindrance to achieving long-term sustainable growth. Additionally, having a narrow productive base and limited resources can make such cities very susceptible to exogenous shocks. Some authors have pointed out how growth dynamics among SMCs differ from other cities. For example, Eeckhout (2004) noted that, while the size distribution of cities remained relatively stable over time, the standard deviation of population growth for larger cities was found to be four to five times smaller than that of the smaller cities. González-Valet al. (2013), in their examination of cities in Europe and the United States over the period 1900–2010, also note that growth patterns among cities differ based on their size. Specifically, they find that small cities grow faster in times of economic crisis, and large cities grew faster during booms.[13] Nevertheless, very few studies have focused exclusively on examining growth patterns among SMCs in a systematic way. Partridge et al. (2008) study how proximity to urban agglomeration affects contemporary population growth in smaller hinterland U.S. counties. Their results show strong negative growth effects associated with being far from higher-tiered urban areas, with significant, but lesser effects of distance to a city's market potential.[14] Another paper that considers only small cities is Devadoss and Luckstead (2015), who find that smaller cities generally follow Gibrat's Law; however, their conclusion is based on a relatively narrow period of growth (2000–2010) and hence they do not include the post-Great Recession period, something we do in the present article.[15] Apart from focusing on growth in a region dominated by small urban places, we examine growth in two distinct periods: short term or postrecovery (2010–2015), and longer term (1990–2010 and 2015).[16] In so doing, we hope to have a deeper understanding of the dynamics of SMCs in the New England region.

DATA

To carry out the analysis we use U.S. Census data on incorporated Places and Minor Civil Divisions (MCDs) as our unit of analysis. U.S. Census definitions of incorporated places and Minor Civil Divisions (MCDs) are based on governmental or administrative units. These can include villages, towns, incorporated cities, and boroughs. Figure 3 shows a map of the region and its main municipalities, along with Boston, its largest city, and New York as a reference (although New York is not part of New England).

Data are taken primarily from the U.S. Census Bureau for New England states of Massachusetts (MA), Connecticut (CT), and Rhode Island (RI) using five, four-year

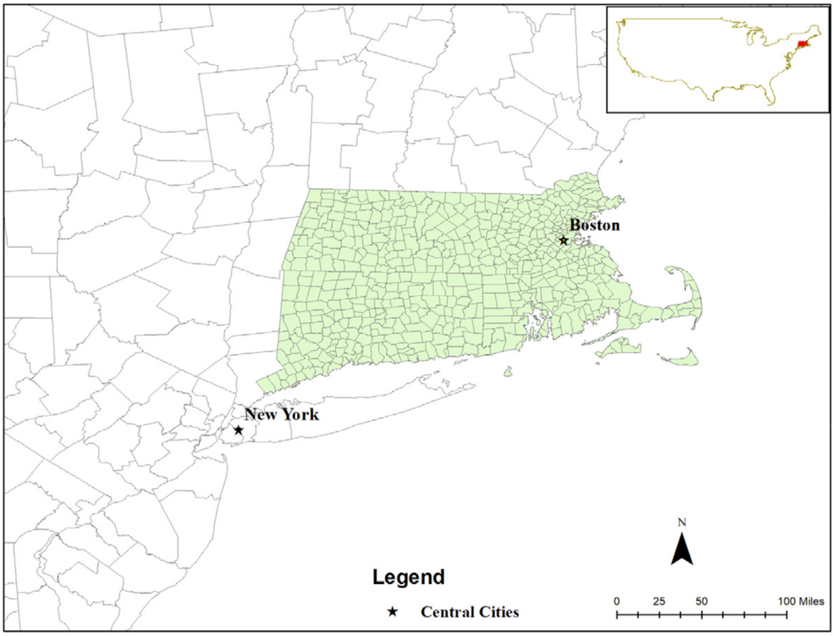

FIG. 3. Incorporated places and MCDs in the selected New England Region
[Color figure can be viewed at wileyonlinelibrary.com]
Notes: Figure 3 shows incorporated places in the states of Massachusetts, Connecticut, and Rhode Island, relative to the major central cities of Boston and New York.

averages (1976–1980, 1986–1990, 1996–2000, 2006–2010, and 2011–2015). While there is no agreement on the appropriate interval for averaging census data (Temple 1999), one of the advantages of using averaged data is that it reduces the influence of shorter-term shocks and swings in the business cycle (Bonnefond 2014; Ding and Knight 2011). In our sample of the New England area, there are 559 contiguously incorporated places. However, we use Henderson (1997) and the United Nations definition of small cities and towns to establish an upper bound of urban locations with population levels of 500,000.[17] We also consider the U.S. Census Bureau's definition of Urban Clusters (UC) to establish a lower bound; we identify urban areas with a minimum population of 2,500 persons. Based on this, we exclude Boston and 86 smaller incorporated places, with an average population of 1,331. By excluding these smaller places we also reduce the potential of skewed growth rates given the very small population of these locations. This leaves a sample of 472 incorporated places, which represents 93 percent of the total population among New England places. The empirical analysis based on incorporated places has been favored by Michaelset al. (2012) and Chen et al. (2018). MDCs have the advantage of capturing both social and political dimensions of urban trends relative to other statistically based definitions of urban locations, and as such can potentially capture the impact of heterogeneity in urban policy among urban communities.

Summary statistics for the variables used for estimation are provided in Table A1. Our key dependent variables are the growth in relative population and real income per capita.[18] We observe a very close correlation between both variables over time

(Figures A1–A4), consistent with previous findings by González-Val (2015). Key explanatory variables used to test for conditional convergence include geographic variables such as distance to large city area (Boston and New York, as a measure of proximity to a large market), long-term January and July temperature levels, and distance to the coast. These last two variables are meant to capture the effects of amenities. Distance to major airports (Figure A5), highlights the importance of logistics and connectivity to urban areas, while rail density per urban area is used to capture ground transport connectivity and investment in local infrastructure. We also include measures that have the potential to increase productivity in urban areas. These include the availability of human capital (measured by the percentage of the adult population with college degrees), lagged unemployment levels, and measures of industrial diversity. The later variable has been used in Glaeser et al. (1992) and Duranton and Puga (2004) among others.

Industrial diversity is calculated as 1 – Herfindahl Index (HHI):

$$\text{Diversity Index} = 1 - \sum_{m-1}^{M} \left[\frac{E_{mi}}{\sum_{m=1}^{M} E_{mi}} \right]^2, \tag{1}$$

where $\frac{E_{mk}}{\sum_{m=1}^{M} E_{mk}}$ represents the ratio of employment in industry m relative to employment in all M industries located in city i. This diversity index will approach one when employment in a city is spread over a wide range of industries and zero when employment is concentrated in a few industrial sectors. We also include controls for key characteristics of urban areas such as acreage of the area covered by water and land size in square meters, which is used as a measure of urban sprawl.

METHODOLOGICAL APPROACH

First, our research strategy focuses on formally testing for random growth among SMCs in the New England region. Specifically, we test for the presence of Gibrat's Law, which predicts that growth among cities is independent of city size. Random growth tests can be carried out using parametric and nonparametric models. We estimate a baseline parametric model of Gibrat's Law based on Equation (2),

$$g_i = \gamma_0 + \gamma_1 rs_i + \epsilon_i, \tag{2}$$

where g_i represents normalized growth rate in population levels for city i, as a function of the relative size of city i and is given by rs_i; with ϵ_i (errors) assumed to be *i.i.d.* Gibrat's Law is said to hold if city growth rate is independent of its relative size, that is, $\gamma_1 = 0$. We follow Eeckhout (2004) by estimating Equation (2) using cross-sectional data.

For nonparametric estimates, we follow Eeckhout (2004), Ioannides and Overman (2003), and González-Val et al. (2014) by estimating an Epanechnikov kernel regression based on Equation (3).

$$g_i = m(rs_i) + \epsilon_i. \tag{3}$$

In this case, g_i is the standardized growth rate of city i, and $m(rs_i)$ is the kernel estimate of relative city size conditional on rs_i (relative city size). In this case, we do not make any parametric assumptions about the functional form of m. The estimate of $m(rs)$ is denoted by $\hat{m}(rs)$, which is considered a local average around the point rs. The Nadaraya–Watson method is used to estimate $\hat{m}(rs)$ based on Hardle and Mammen (1993) and it is given by Equation (4),

$$\hat{m}(rs) = \frac{n^{-1}\sum_{i=1}^{n} K_h(rs - rs_i)g_i}{n^{-1}\sum_{i=1}^{n} K_h(rs - rs_i)}, \tag{4}$$

where K_h represents the dependence of the Kernel (K) on the bandwidth h. We utilize the bandwidth of $h = 0.5$ as recommended by Silverman and Bernard (1986). With an estimated mean of $\hat{m}(rs)$, we can also generate a Kernel-based estimate of the variance in growth rate again using the Nadaraya–Watson method. In this case, the variance in growth is given by Equation (5);

$$\widehat{\sigma^2}(rs) = \frac{n^{-1}\sum_{i=1}^{n} K_h(rs - rs_i)(g_i - \hat{m}(rs))^2}{n^{-1}\sum_{i=1}^{n} K_h(rs - rs_i)}. \tag{5}$$

One of the shortcomings of this method is that it is very sensitive to atypical values. However, we alleviate this problem by removing urban locations with population levels below 2,500 and greater than 500,000 (González-Val et al. 2014).

As Gabaix and Ioannides (2004) highlight, if Gibrat's Law is assumed to hold, then the distribution function from which any city of size S is selected will have a mean and variance that are independent of size S. This implies that nonparametric estimates of mean growth relative to city size should be a straight line along the value of zero. Any deviations from zero can be considered a deviation from the mean, and therefore reflect the sensitivity of growth to city size. Similarly, we can test for constant variance, which again should result in a straight line along the value of one. Finally, for these tests, we generate bootstrapped 95 percent confidence bands, which are calculated based on 500 random sample draws with replacement.

TESTING FOR BETA CONVERGENCE

Convergence theories predict that smaller size cities will grow at a faster rate than larger ones, as growth rates among cities converge to some long-term level. Traditional tests for beta-convergence are based on Barro (1991) and Barro and Sala-i-Martin (1991) estimation of Equation (6).

$$\log\left(N_{it+1}/N_{it}\right) = \beta_0 + \beta_1 logN_{it} + \epsilon_{it}, \tag{6}$$

where $\log(N_{it+1}/N_{it})$ captures the logarithmic growth rate between time period t and $t+1$, and N_{it} represents the initial period (relative) population levels. Absolute convergence occurs if $\beta_1 < 0$, which implies that locations with smaller initial population levels grow at a faster rate than places with higher initial population levels.[19] Tests for convergence in population levels can be easily adapted to test for convergence in real per capita income, where the dependent variable can be rewritten in terms of growth in real per capita income.

Equation (6) can be adapted to test for conditional convergence in both population and real per capita income levels based on Equation (7),

$$\log(N_{it+1}/N_{it}) = \beta_0 + \beta_1 logN_{it} + \gamma' X_{it} + \epsilon_{it}. \tag{7}$$

We are particularly interested in the sign and magnitude of the vector X_{it} of conditional variables which can also influence the growth process (population or real per capita income) of cities. Duranton and Puga (2014) highlight the dangers of estimation of Equation (7) using cross-sectional data, such as correlated omitted variables, reserve causation, and endogeneity, all of which can bias estimation results. To address this problem and verify the robustness of our estimates, we exploit the panel dimension of the data and re-estimate Equation (7) using Fixed Effects and General Methods of Moments (GMM) techniques. Based on the exclusion criteria (see Wooldridge 2015) instruments should be unrelated to the dependent variable g_i apart from its effect on key explanatory variables C_{it}. In this case, the instruments Z_{it}, will be unrelated to the error term.[20]

We adapt Glaeser and Saiz (2003) and Moretti (2004) and instrument for percent college-educated by calculating the average distance of each urban area to the nearest land grant college. Land grant colleges were first established more than 100 years ago by Morrill Act of 1862 and are argued to have been established based on convenience and accessibility for local communities. As such, distance to land grant colleges can be considered exogenous to current growth at the city level growth (Moretti 2004). Additionally, we hypothesize that universities follow the development patterns of land grant colleges, and regions that eventually develop as college towns and centers of innovation with a high level of college-educated will be linked to proximity to a grant college (see Figure A6). Second, we also include 1980 values of percent college-educated for each urban place as a predictor of present-day college-educated. Additionally, since present-day transport infrastructure can be influenced by current and past populations and income growth patterns, we predict current estimates of transportation networks using historical railway patterns in the United States over the period 1826–1911 taken from Atack (2015) (see Figure A7).

One of the shortcomings of models using cross-sectional data is the inability to control for unobserved characteristics which may bias our estimates. To address this problem and possible unobserved heterogeneity across urban locations, we use the full panel dataset and estimate fixed-effects regressions given by Equation (8), where a_i and l_t represent city and time fixed effects, respectively:

$$\log(N_{it+1}/N_{it}) = \beta_0 + \beta_1 logN_{it} + \beta_2 X_{it} + a_i + l_t + \epsilon_i. \tag{8}$$

While fixed effects models have the advantage of capturing long-term trends and controlling for unobserved heterogeneity, this estimation method comes at a price, specifically the exclusion of locational explanatory variables, given that these variables seldom change over time. However, this allows us to focus on assessing the impact of factors that may be much more endogenous to policy changes. Unfortunately, if changes in explanatory variables over time are strongly correlated with unexplained factors as captured in the error term, fixed effects estimators are also biased (Duranton and Puga 2014). To address this issue and as a final robustness check, we utilize Arellano–Bover/Blundell–Bond (Arellano and Bover 1995; Blundell and Bond 1998) dynamic panel estimators which use past values of explanatory variables as well as external variables as instruments in the GMM estimation see Roodman (2009) for details on dynamic panel models.

RESULTS

TESTS FOR GIBRAT'S LAW

Results of nonparametric kernel estimates relating standardized growth rates in population levels to relative city size are presented in Figure 4, Panels A–D. During the postrecovery period (Figure 4, Panel A), we note fairly stable population growth rates across city sizes. However, over the longer term (1990–2010), smaller urban locations are found to have higher rates of population growth relative to larger ones. Nonparametric estimates relating variance in growth rates and relative city size also highlight higher levels of variation in growth rates, particularly among smaller urban communities during the postrecovery period and over the longer term (Figure 4, Panels B and D). Therefore, in both instances, we find a negative relationship between population growth, as well as the variance in population growth, and city size. These results confirm the findings of Eeckhout (2004) and González-Val et al. (2014) of higher variability in growth among smaller locations particularly over the longer term (Figure 4, Panels C and D).

Results of parametric tests for Gibrat's Law based on Equation (2) confirm those of nonparametric estimates. Specifically, parametric tests fail to reject random growth (Gibrat's Law) only over the short term (2010–2015). Gibrat's Law is rejected for longer-term population growth at a 1 percent significance level (Table 1). This result suggests that locations with smaller initial population levels grow at a faster rate than larger urban areas over the longer term.

PARAMETRIC TESTS FOR CONDITIONAL CONVERGENCE

Results of formal tests for conditional convergence in population levels during the postrecovery period (2010–2015) and over the longer term (1990–2010 and 1990–2015) are reported in Table 2. As in Glaeser et al. (1995), we do not find evidence that the population of richer cities grew slower, so we reject absolute convergence. We test for conditional convergence by including key locational factors (Columns 1 and 4). In Columns 2 and 4, we include all conditioning variables (locational and alternative factors). Results based on the IV estimation are presented in Columns 3 and 6. Finally, pooled estimates using the full panel data are presented in Column 7. Based on these results, we fail to find evidence of convergence in population levels over the short term but we do observe conditional convergence in population growth rates over the longer term. This result provides supporting evidence that smaller urban places in the New England region grow at a faster rate than larger towns and cities over the long term.

In terms of conditional factors, proximity to a large metro area (Boston and New York) is found to be positively related to recovery in population levels during both the postrecovery period and also over the longer term. This provides strong evidence of the importance of urban centers (and the opportunities included therein), as a draw to people over both the short term and long term. Indeed, a similar conclusion can be reached when examining the negative and significant relationship found between initial

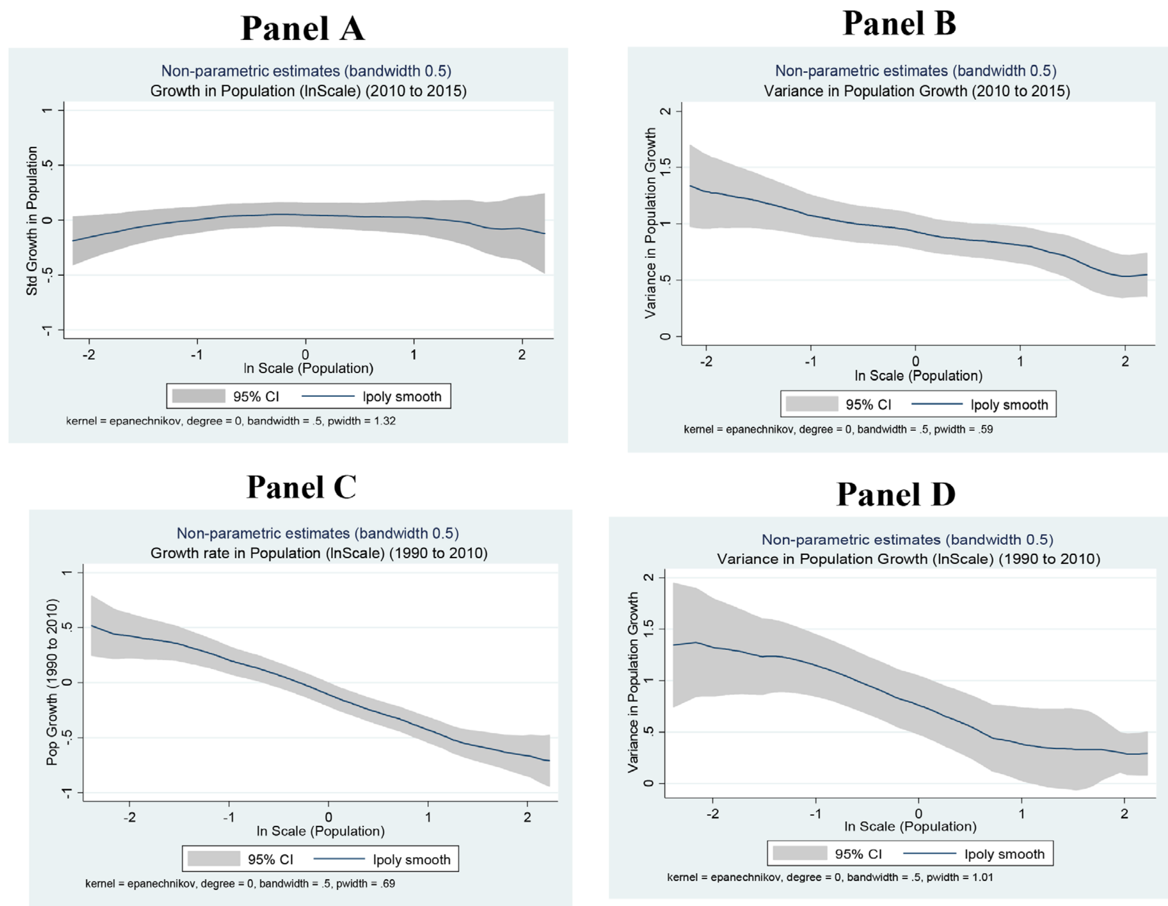

FIG. 4. Results of nonparametric estimation on population growth relative to city size (ln scale).
[Color figure can be viewed at wileyonlinelibrary.com]

Notes: Figure 4 outlines results of nonparametric estimates which relates growth in population level and measures of relative city size over the short and long terms (Panels A and C). We also provide nonparametric estimates which relate variance in population growth and relative city size over the short and long terms (Panels B and D). In both instances we find a negative relationship between population growth, as well as the variance in population growth, and city size.

TABLE 1. Results of Parametric Tests for Gibrat's Law—Growth in Population

	(1) Growth in population (ln scale) (1990–2010)	(2) Growth in population (ln scale) (2010–2015)	(3) Growth in population (ln scale) (1990–2015)
Population (ln scale) lag 1[1]	−0.266***	0.0247	−0.163***
	(0.045)	(0.016)	(0.048)
State FE	**Yes**	**Yes**	**Yes**
N	**472**	**472**	**472**
R^2	**0.076**	**0.2182**	**0.022**
adj. R^2	**0.070**	**−0.001**	**0.020**

Notes: Table 1 outlines the results of parametric tests for Gibrat's Law on growth in population levels. Tests are executed for the three periods, postrecovery (2010–2015), and long term (1990–2010, and 1990–2015). Errors are clustered at the municipal levels. Standard errors in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

unemployment levels and population growth during the short-term postrecovery period (Table 4, Column 6). This result suggests a tendency for individuals living in areas with high initial unemployment levels (or low productivity) to migrate to lower unemployment locations, particularly during the postrecovery period, a finding consistent with past research by Glaeser et al. (1995).

In terms of amenities, a one Celsius increase in long-term summer temperature levels, in particular, is associated with a 1.3 percent increase in population growth during recovery and as much as a 3 percent increase over the longer term.[21] This result highlights the importance of temperature amenities to population growth and suggests that when people move they tend to move to locations with more moderate temperature levels. Interestingly, a 10 percent reduction in distance to coastal regions is associated with a 0.1 percent decrease in population growth over the long term and a 0.04 percent over the short term, which suggests that proximity to coastal amenities is not an important draw to population growth in the New England region. Indeed, at the national-level (Crossett et al. 2004) found warmer coastal locations in the Southeast and West coast regions of the United States to be the most attractive for population migration, particularly by retirees and job seekers.

Another particularly interesting result is the lack of a significant effect of infrastructure, particularly transport infrastructure (measured in terms of rail density) on population growth.[22] We do find that distance to major regional and international airports to be negatively associated with growth, perhaps a counter-intuitive result since distance to major airports have traditionally been associated with growth in employment and human capital among some North American regions (Chen et al. 2018; Florida et al. 2015; Green 2007). However, these findings are largely confirmed by the results of alternative specifications and pooled OLS–IV (GMM) (Table 2, Column 7), which utilize the full panel data set and can be interpreted as results reflecting longer-term trends.

We find little or no impact of human capital on population growth, a significant difference with Glaeser et al. (1995). Given the problems of omitted variable bias and unobserved heterogeneity across urban places, we again leverage the panel dataset and re-estimate this relationship utilizing fixed-effects model. Results of Arellano–Bond and Arellano–Bover/Blundell–Bond dynamic panel model estimator (Arellano and Bond

TABLE 2. Results of OLS, IV (GMM)—Growth in Population Levels

	1	2	3	4	5	6	7
	OLS Growth in population (ln scale) (1990–2010)	OLS Growth in population (ln scale) (1990–2010)	IV (GMM) Growth in population (ln scale) (1990–2010)	OLS Growth in population (ln scale) (2010–2015)	OLS Growth in population (ln scale) (2010–2015)	IV (GMM) Growth in population (ln scale) (2010–2015)	Pooled IV (GMM) Growth in population (ln scale) (1990–2015)
Population level	−0.053***	−0.051***	−0.052***	−0.001	−0.000	0.000	−0.032***
(ln scale) lag1[1]	(0.006)	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)	(0.003)
Real per capita income	−0.008	−0.039	0.004	0.018***	0.008	0.006	−0.021
(ln scale) lag[2]	(0.018)	(0.051)	(0.051)	(0.004)	(0.009)	(0.015)	(0.019)
Geographic factors							
ln(distance to city)	−0.033***	−0.034***	−0.039***	−0.016***	−0.015***	−0.015***	−0.019***
	(0.010)	(0.010)	(0.010)	(0.002)	(0.002)	(0.002)	(0.004)
ln(distance to airport)	0.022**	0.026**	0.032***	0.006***	0.006***	0.007***	0.013***
	(0.009)	(0.010)	(0.010)	(0.002)	(0.002)	(0.002)	(0.004)
ln(distance to coast)	0.011*	0.011*	0.011*	0.004***	0.004***	0.003***	0.004
	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)	(0.003)
ln(rail density)	−0.002	−0.002	−0.001	0.000	0.000	−9.01E-05	0.000
	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)
January Lt temp	0.023***	0.023***	0.021***	−0.001	−0.001	−0.001	0.011***
	(0.007)	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)	(0.003)
July Lt temp	0.029***	0.029***	0.035***	0.014***	0.013***	0.013***	0.019***
	(0.010)	(0.010)	(0.009)	(0.002)	(0.002)	(0.002)	(0.004)
Alternative explanatory variables							
Industrial diversity lag1[1]		0.249	0.238		0.047	0.06	−0.058
		(0.214)	(0.209)		(0.048)	(0.056)	(0.054)
Percent college educated		0.000	−0.001		0.000	0.000	0.000
lag 1[1,2]		(0.001)	(0.001)		(0.000)	(0.000)	(0.000)
Unemployment lag1[1]		−0.005	−0.008		−0.001***	−0.001***	0.000
		(0.005)	(0.005)		(0.000)	(0.000)	(0.001)
City controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
State FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year FE	**No**	**No**	**No**	**No**	**No**	**No**	**Yes**
Observations	**472**	**472**	**472**	**472**	**472**	**472**	**1,888**
R^2	**0.284**	**0.289**	**0.283**	**0.476**	**0.490**	**0.489**	**0.236**

Notes: Table 2 reports the results of OLS, IV (GMM), pooled IV (GMM) of tests for conditional convergence in population growth. ln scale refers to log standardized relative population and income levels of a city. Errors are clustered at the municipal level and standard errors are in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[1]Lagged values vary according to the base year, 2010 and 1990 (except for pooled IV GMM).

[2]Percent college educated is Instrumented using distance to land grant colleges, and percent college educated in 1980.

[3]Rail density is instrumented using rail density levels in 1820–1911.

TABLE 3. Results of FE and Dynamic Panel (GMM), Growth in Population Levels

	1 FE Growth in population (ln scale) (1990–2015)	2 Dynamic panel Growth in population (ln scale) (1990–2015)
Variables		
Population level (ln scale) lag1	−0.524***	−0.315***
	(0.016)	(0.069)
Real per capita income (ln scale) lag1	−0.002	−0.519***
	(0.020)	(0.107)
Industrial diversity lag1	−0.067	−0.375***
	(0.055)	(0.101)
Percent college educated lag 1[1]	0.002***	0.008***
	(0.000)	(0.002)
Unemployment lag1	0.001*	−0.002
	(0.001)	(0.001)
City controls	**Yes**	**Yes**
State FE	**Yes**	**Yes**
Year FE	**Yes**	**Yes**
Arellano–Bond test for AR(1) in first differences	–	**0.000**
Arellano–Bond test for AR(2) in first differences	–	**0.314**
Hansen test of overid. restrictions: chi2(15)		**0.000**
Observations	**1,888**	**1,888**

Notes: Table 3 outlines the results of FE, dynamic panel (GMM) models of conditional convergence in population growth over the long term (1990–2015). Errors are clustered at the municipal level. Standard errors in parentheses The Hansen J test are the *p*-values for the null. hypothesis, valid specification. Instruments used for GMM (Column 2) are based on first differences of population (ln scale), *t*−1, *t*−2, & *t*−3, ln(PCTCollege) *t*−2, ln(Div) *t*−1, (Unemploy) *t*−1 and all further lags. Additional instruments used for levels equations in SYS-GMM using ln(distance to land grant colleges), and percent college educated in 1980.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

1991; Blundell and Bond 1998) are also listed in Table 3, Column 2. The results of both models highlight the positive association between our measures of human capital and population growth. For FE models, a 10 percent increase in percent college in the prior period is associated with an increase in population growth of approximately 2 percent. This result confirms findings by Glaeser (2005) and Glaeser and Resseger (2010) of a tendency of persons to locate in urban areas where highly educated workers to settle. This can be in part due to potential positive externalities such as higher productivity and income benefits or lower risk of crime. Results of dynamic panel models also predict a negative association between industrial diversity and population growth, suggesting that areas with more diverse industries (manufacturing and services) tend to experience lower rates of population growth, a puzzling result that contradicts some of the literature. However, while AR (2) tests confirm no serial correlation on first differenced errors, J-Hansen's tests for overidentification suggests that these results are indeed weakened by instruments which are correlated with the error term.

We also test for conditional convergence in real per capita income (Table 4). Based on the results of OLS and IV (GMM) estimates, we find evidence of conditional convergence in real per capita income growth over both the short and long term. Specifically, a 10 percent reduction in initial real per capita income is associated with as much as 2.6 percent

TABLE 4. Results of OLS, IV (GMM), Growth in Real Income Levels

	1	2	3	4	5	6	7
	OLS Growth in real income (ln scale) (1990–2010)	OLS Growth in real income (ln scale) (1990–2010)	IV (GMM) Growth in real income (ln scale) (1990–2010)	OLS Growth in real income (ln scale) (2010–2015)	OLS Growth in real income (ln scale) (2010–2015)	IV (GMM) Growth in real income (ln scale) (2010–2015)	Pooled IV (GMM) Growth in real income (ln scale) (1990–2015)
Population level	−0.049***	−0.046***	−0.045***	−0.011**	−0.0120**	−0.0140**	−0.019***
(ln scale) lag1[1]	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.002)
Real per capita income	−0.040**	−0.217***	−0.191***	−0.028*	−0.221***	−0.260***	−0.202***
(ln scale) lag[2]	(0.020)	(0.051)	(0.055)	(0.017)	(0.046)	(0.052)	(0.031)
Geographic factors							
ln(distance to city)	−0.035***	−0.033***	−0.032***	−0.016*	−0.012	−0.011	−0.020***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.004)
ln (Distance to	0.030***	0.032***	0.031***	−0.004	−0.005	−0.006	0.010***
Airport)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.003)
ln(distance to coast)	−0.022***	−0.022***	−0.022***	0.007	0.006	0.005	−0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.002)
ln(rail density)[1]	0.000	0.000	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
January Lt temp	0.003	0.004	0.003	−0.000	−0.000	0.000	0.000
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.002)
July Lt temp	0.020**	0.017**	0.015*	0.007	0.001	0.000	0.008***
	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.003)
Alternative explanatory variables							
Industrial diversity		0.590**	0.451**		0.886***	0.997***	0.507***
lag1[1]		(0.233)	(0.225)		(0.232)	(0.240)	(0.066)
Percent college		0.003***	0.003**		0.004***	0.005***	0.004***
educated lag 1[1,2]							
		(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Unemployment lag1[1]		−0.006	−0.006		−0.000	0.000	−0.002*
		(0.004)	(0.004)		(0.002)	(0.002)	(0.001)
State FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year FE	**No**	**No**	**No**	**No**	**No**	**No**	**Yes**
Observations	**472**	**472**	**472**	**472**	**472**	**472**	**1,888**
R^2	**0.343**	**0.389**	**0.385**	**0.044**	**0.135**	**0.13**	**0.156**

Notes: Table 4 reports the results of OLS, IV (GMM), pooled IV (GMM) of tests for conditional convergence in real income growth over key periods, postrecovery, and longer term. Errors are clustered at the municipal level, and standard errors are in parentheses.

$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[1]Lagged values vary according to the base year, 2010 and 1990 (except for Pooled IV GMM).

[2]Percent college educated is instrumented using distance to land grant colleges, and percent college educated in 1980.

[3]Rail density is instrumented using rail density levels in 1820–1911.

TABLE 5. Results of FE, Dynamic Panel (GMM), Growth in Real Income

	1 FE Growth in real income (ln scale) (1990–2015)	2 Dynamic Panel Growth in real income (ln scale) (1990–2015)
Variables		
Population level (ln scale) lag1	0.077***	−0.025**
	(0.019)	(0.005)
Real per capita income (ln scale) lag1	−0.921***	−0.149***
	(0.035)	(0.042)
Industrial diversity lag1	0.037	1.352***
	(0.065)	(0.267)
Percent college educated lag 1[1]	0.005***	0.003***
	(0.001)	(0.000)
Unemployment lag1	−0.002	0.046
	(0.002)	(0.033)
City controls	**Yes**	**Yes**
State FE	**Yes**	**Yes**
Year FE	**Yes**	**Yes**
Arellano–Bond test for AR(1) in first differences	–	**0.000**
Arellano–Bond test for AR(2) in first differences	–	**0.488**
Hansen test of overid. restrictions: chi2(15)		**0.07**
Observations	**1,888**	**1,888**

Notes: Table 5 outlines the results of FE, dynamic panel (GMM) models of conditional convergence in population growth over the long term (1990–2015). Errors are clustered at the municipal level. Standard errors in parentheses The Hansen J test are the *p*-values for the null. hypothesis, valid specification. Instruments used for GMM (Column 2) are real per capita income [ln scale], $t-1$, & $t-2$, are ln(PCTCollege), $t-1$, & $t-2$, ln(Div), $t-1$, & $t-2$, (Unemploy), $t-1$, & $t-2$, and all further lags. Additional instruments used for levels equations in SYS-GMM using ln(distance to land grant colleges), percent college educated in 1980 and ln(road density 1947).
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

increase in real per capita income earnings, suggesting that smaller regions experience convergence in income and productivity over the short and longer terms.

In terms of other key factors, the importance of human capital and industrial diversity cannot be undervalued over both the short-term post-Great Recession period and over the longer term. We find that more educated cities experience faster income growth as in Glaeser et al. (1995) and Barro (1991). For instance, a 10 percent increase in lagged percent college-educated during the recovery period is associated with a 5 percent increase in real income levels in the short term and a 4 percent increase over the long term. This highlights the importance of retaining skilled human capital in order to generate future productivity and growth within cities and facilitating faster recovery during difficult times. Similarly, a 10 percent increase in initial industrial diversity is associated with a 10 percent increase in real per capita income during the postrecovery period and a 5 percent increase over the longer term. This finding supports the view that having greater diversity among businesses can help cushion the negative impacts of economic cycles and can also promote greater economic wellbeing among cities (Attaran 1986). They are also consistent with Glaeser et al. (1992), who find evidence that cross-industry intellectual externalities are particularly important to explain urban growth, at least between 1960 and 1990.

TABLE 6. Assessing the "Legacy" Effect on Population and Real Income Growth

	1 OLS Growth in population (ln scale) (1990–2010)	2 OLS Growth in population (ln scale) (2010–2015)	3 OLS Panel Growth in population (ln scale) (1990–2015)	4 OLS Growth in real income (ln scale) (1990–2010)	5 OLS Growth in real income (ln scale) (2010–2015)	6 OLS Panel Growth in real income (ln scale) (1990–2015)
Variables						
Population level	−0.052***	−0.000	−0.032***	−0.047***	−0.015***	−0.022***
(ln scale) lag1[1]	(0.006)	(0.001)	(0.003)	(0.006)	(0.006)	(0.002)
Real per capita income	−0.0571	0.012	0.003	−0.187***	−0.147**	−0.134***
(ln scale) lag[1]	(0.054)	(0.009)	(0.011)	(0.057)	(0.058)	(0.035)
Alternative factors						
Percent college educated	0.001	0.000	0.001**	0.003**	0.002**	0.003***
lag 1[1]	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment lag1[1]	−0.005	−0.001***	−0.001	−0.005	−0.001	−0.002*
	(0.005)	(0.001)	(0.001)	(0.004)	(0.002)	(0.001)
Manufacturing	0.001	0.002	0.001	−0.010	−0.001	−0.007*
concentration in 1980	(0.013)	(0.002)	(0.005)	(0.010)	(0.010)	(0.004)
Additional conditional variables[2]	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
City controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
City FE	**No**	**No**	**Yes**	**No**	**No**	**Yes**
State FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year FE	**No**	**No**	**Yes**	**Yes**	**No**	**Yes**
N	**472**	**472**	**1,888**	**472**	**472**	**1,888**

Notes: Table 6 outlines tests assessing the impacts of early specialization in manufacturing among municipalities on growth in population and real income levels over the longer-term and postrecovery period. Errors are clustered at the municipal level and standard errors are in parenthesis.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

[1]Lagged values vary according to the base year, 2010 and 1990, except in the case of dynamic panel models.

[2]Conditioning variables include the log of distance to the central city, and coastal boundaries, rail density, January and July long-term temperature levels.

Other key factors relevant for long-term real income growth include proximity to central city area and coastal amenities, and higher average January and July temperature levels. Individuals located closer to the central city district benefit from higher productivity and earnings, as do locations with more amenable temperature levels. Interestingly, individuals located closer to the coast also benefit from higher earnings and this may stem from the attraction of these locations to more wealthy residents in the New England region. These results are largely confirmed based on the results of IV (GMM) and Pooled OLS-IV (GMM) models (Table 4, Column 7). One difference between pooled and cross-sectional estimates is the negative relationship between growth in unemployment rates and real per capita income growth estimated in the panel models. This result confirms that areas with lower productivity levels also tend to have lower rates of per capita income growth. As a further robustness test, fixed effects and dynamic panel models largely confirm these results, indicating a positive association between quality of human capital and industrial diversity, and real income per capita growth (Table 5). For dynamic panel models in particular results of AR (2) tests confirm no serial correlation on first differenced errors, while J-Hansen's tests show the validity of instruments at the 5 percent significance level.

ESTIMATING THE "LEGACY" EFFECT

The last step is to assess possible differential growth dynamics among communities with past specialization in manufacturing, relative to other communities in the New England region. We refer to this impact as the "legacy effect."[23] We identify such manufacturing centers as urban regions where employment in manufacturing is more than one standard deviation above the national average of 41 percent in 1980. While the decline in manufacturing is already well underway in this year, based on our analysis we find 126 locations in the sample that meet this criterion. The average population level within these urban areas was estimated at 20,350, with average employment in manufacturing reaching as high as 57 percent of the labor force in 1980 (Table A2). We replace our measure of industrial diversity with a dummy variable taking a value of one for locations found to have early specialization in manufacturing and zero otherwise. We, therefore, consider this a conservative estimate of the "legacy" effect.

Table 6 highlights the results of the "legacy" effect. We find little differences in the performance among locations in terms of population and real income growth over the short term. However, we find that areas which can be considered manufacturing centers in 1980 experienced, on average, 0.7 percentage points lower real income growth relative to less specialized manufacturing urban locations in the New England region over the long term. This result suggests that prior specialization in manufacturing continues to have a dampening impact on productivity over the long term.

CONCLUSIONS

This article examines the growth dynamics of small and medium urban places in the New England region, focusing on the post-Great Recession (2010–2015) and longer-term growth period (1990–2010 and 2015). We find higher levels of growth and variability in population and real income growth among smaller urban locations. We also find evidence of convergence population growth rates over the longer term, and convergence in real income growth during the postrecovery period and longer term. This result highlights the relatively slower rates of recovery in population levels relative to real incomes over the short term. This provides strong empirical support for convergence-based theories rather than random growth models over the longer term among smaller urban locations.

In terms of key determinants of growth, we find proximity to the city center and higher summer temperature amenities to be positively associated with population growth over both the short and longer term. Urban locations located further away from coastal boundaries and major airports also experience higher rates of population growth. These factors highlight the importance of key locational factors as determinants of population growth. Not surprisingly, locations with high levels of unemployment levels in the prior year are also associated with lower rates of population growth during the short term. This suggests a relocation of population away from low productivity centers during the postrecovery period.

We also find convergence in real income growth over both the short and longer terms. Factors such as percent of college-educated population and industrial diversity are positively associated with growth in productivity levels (real income) during postrecovery and over the longer term. Other factors such as proximity to the city center and coastal boundaries and higher long-term summer temperature amenities are positively associated with income growth over the longer term. Robustness checks based on instrumental variables, fixed effects and dynamic panel models confirm the importance of these variables in determining growth in population and real income levels.

These results highlight the importance of key locational factors, in particular, distance to the city center and temperature amenities to population and real income growth. More importantly, human capital endowments and industrial diversity are found to sustain growth in real income over both the short and longer terms. This suggests that policies geared to building new and diverse industries, as well as attract and retain qualified personnel, can be key to sustaining growth among small urban areas over both the short and longer terms. Finally, in terms of the "legacy effect", we find that locations with early specialization in manufacturing grew on average less in terms of real per capita income than other more industrially diverse locations over the long term.

Notes

[1]Nua.unhabitat.org. (2019). *Implementing the New Urban Agenda: Projects.* [online] Available at: http://nua.unhabitat.org/pillars.asp?PillarId=15&ln=1 [Accessed 20 May 2019].

[2]The United Nations defines SMCs as urban areas with population levels below 500,000. We follow this definition throughout the paper.

[3]See https://www.bostonfed.org/workingcities/index.htm

[4]Authors estimates based on recent ACS poverty level data.

[5]Authors estimates based on recent ACS poverty level data.

[6]For a comprehensive summary of this literature, see Duranton, Gilles, and Diego Puga. 2014. "The Growth of Cities." *Handbook of Economic Growth* 2:781–853.

[7]A detailed review of the evidence on Gibrat and Zipf's Laws can be found in Gabaix, Xavier, and Yannis M Ioannides. 2004. "The evolution of city size distributions." *Handbook of regional and urban economics* 4:2341-78.

[8]See Zipf, George Kingsley. 1949. “Human behaviour and the principle of least-effort. Cambridge MA edn.” *Reading: Addison-Wesley*, ibid.

[9]Eeckhout, Jan. 2004. “Gibrat’s law for (all) cities.” *The American Economic Review* 94(5):1429–51, ibid. finds that, when using the entire distribution of U.S. cities, the log-normal distribution is more appropriate than the Pareto one (the statistical distribution implied by Zipf’s Law) to fit the data. While Giesen, Kristian, Arndt Zimmermann, and Jens Suedekum. 2010. “The size distribution across all cities–double Pareto lognormal strikes.” *Journal of Urban Economics* 68(2):129–37, ibid. finds that the double Pareto log-normal distribution provides a better fit to their sample of cities drawn from eight countries,

[10]See Barro, Robert J., and Xavier Sala-i-Martin. 2004. *Economic growth*. Cambridge, Mass.: MIT Press. ibid. for a review of this vast literature.

[11]A notable exception is De Long, J Bradford, and Andrei Shleifer. 1993. “Princes and merchants: European city growth before the industrial revolution.” *The Journal of Law and Economics* 36(2):671–702. who study how institutions historically affected city performance.

[12]See also Glaeser, Edward L, and Albert Saiz. 2003. “The rise of the skilled city.” National Bureau of Economic Research., who emphasize the role played by human capital in U.S. city growth.

[13]Desmet, Klaus, and Jordan Rappaport. 2015. “The settlement of the United States, 1800–2000: The long transition towards Gibrat’s law.” *Journal of Urban Economics*. note significantly different growth patterns between small and large U.S. counties

[14]In a recent paper Cuberes, David, Klaus Desmet, and Jordan Rappaport. 2018. “Urban Growth Shadows.” study urban growth shadows in 1840-2016 U.S i.e. the phenomenon by which a city grows less if it is located near to a large one.

[15]Specifically, the period 2000 to 2010 includes the Great Recession of (2007 to 2009)

[16]We also consider the long term to include the period 1990 to 2010.

[17]https://esa.un.org/unpd/wup/Publications/Files/WUP2014-Highlights.pdf

[18]We define population and real per capita income in relative term, that is, observed values in city i divided by the sample average or $\frac{S_{it}}{1/N(\sum_{i=1}^{N} S_{it})}$

Conversely, model 5 can be used to test for Divergence in city growth rates, which is confirmed if $\beta_1 > 0$

[19]This latter requirement is referred to as the exclusion requirement (see Angrist, Joshua D, and Jörn-Steffen Pischke. 2008. *Mostly harmless econometrics: An empiricist’s companion*: Princeton university press.)

[20]We also test alternative measures of temperature amenities such as average temperature levels and standard deviation in temperature (results available upon request).

[21]We also examined other measures of infrastructure such as road density as well as instruments to address the problem of reserve causality and omitted variable bias.

[22]Legacy cities are older industrial urban areas that have experienced significant declines in population levels and job losses (see https://www.legacycities.org/ and Mallach, Alan, and Lavea Brachman. 2013. *Regenerating America’s legacy cities*: Lincoln institute of land policy.)

[23]Legacy cities are older industrial urban areas that have experienced significant declines in population levels and job losses (see https://www.legacycities.org/ and Mallach, Alan, and Lavea Brachman. 2013. *Regenerating America’s legacy cities*: Lincoln institute of land policy.)

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APPENDIX:

TABLE A1. Summary Statistics

	Years	Number of Observations	Mean	Standard Deviation
Dependent variables				
Population levels	2015	472	22,431.46	24,958.18
	2010	472	21,954.20	24,504.84
	2000	472	21,402.54	24,078.31
	1990	472	20,398.97	23,973.50
	1980	472	19,358.14	23,568.87
Real income per capita	2015	472	15,961.16	5,130.94
	2010	472	15,999.48	5,130.93
	2000	472	15,901.31	5,513.17
	1990	472	14,045.75	4,516.98
	1980	472	9,767.08	2,468.89
Key locational variables				
Distance to major seaports (miles)		472	26.76	15.24
Distance to coastal boundary (miles)		472	18.52	15.90
Distance to major airports (miles)		472	28.63	15.22
Distance to Boston (miles)		472	57.39	36.26
Road density (MPSqM)		472	47.09	28.39
Rail density (MPSqM)		472	0.84	1.17
January long-term temperature levels (°Celsius)		472	−2.92	1.16
July long-term temperature levels (°Celsius)		472	22.21	0.74
Alternative variables				
Industrial diversity index	2015	472	0.86	0.03
	2010	472	0.86	0.02
	2000	472	0.87	0.02
	1990	472	0.88	0.02
	1980	472	0.84	0.05

(*Continued*)

TABLE A1. Continued

	Years	Number of Observations	Mean	Standard Deviation
Percentage of the population 25 years and over with college and advanced degrees	2015	472	49.73	15.03
	2010	472	47.17	14.95
	2000	472	41.91	14.92
	1990	472	36.08	13.17
	1980	472	21.49	11.29
Unemployment rate	2015	472	7.02	2.44
	2010	472	9.19	2.53
	2000	472	3.88	2.52
	1990	472	5.55	1.96
	1980	472	4.79	1.87

TABLE A2. New England Cities with Employment in Manufacturing One Standard Deviation Higher than the National Average in 1980

	Variable	Obs	Mean	Min	Max
	Percent employment in manufacturing 1				
1	St. dev > national average	126	41.9%	36.0%	57.1%
2	Population	126	20,350.6	1,637.0	142,546.0

Notes: Table A2 outlines the overall distribution of cities included in the sample, highlighting the portion of the distribution of cities where employment in manufacturing is at least one standard deviation higher than the national average.

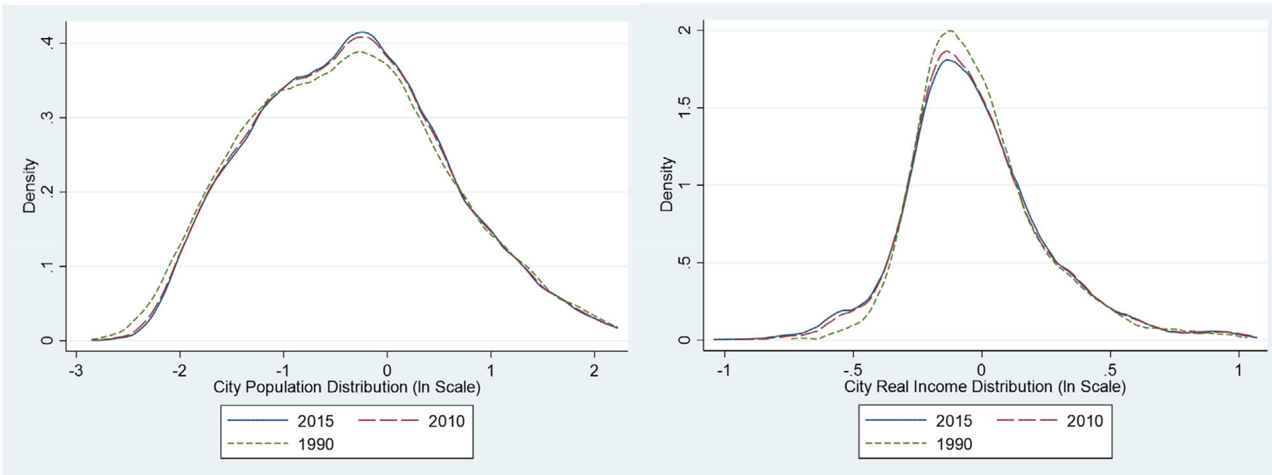

FIG. A1. Kernel density estimation (ln scale) of city population and real income per capita distributions.
(*Source*: ACS from the IPUMS 1980–2015)
[Color figure can be viewed at wileyonlinelibrary.com]

FIG. A2. Stochastic kernel estimates of the relationship between per capita income growth (ln scale) and population growth (ln scale)—2015.
(*Source*: ACS from the IPUMS 2015)
[Color figure can be viewed at wileyonlinelibrary.com]

FIG. A3. Stochastic kernel estimates of the relationship between per capita income growth (ln scale) and population growth (ln scale)—2010.
(*Source*: ACS from the IPUMS 2010)
[Color figure can be viewed at wileyonlinelibrary.com]

FIG. A4. Stochastic kernel estimates of the relationship between per capita income growth (ln scale) and population growth (ln scale)—1990.
(*Source*: ACS from the IPUMS 1990)
[Color figure can be viewed at wileyonlinelibrary.com]

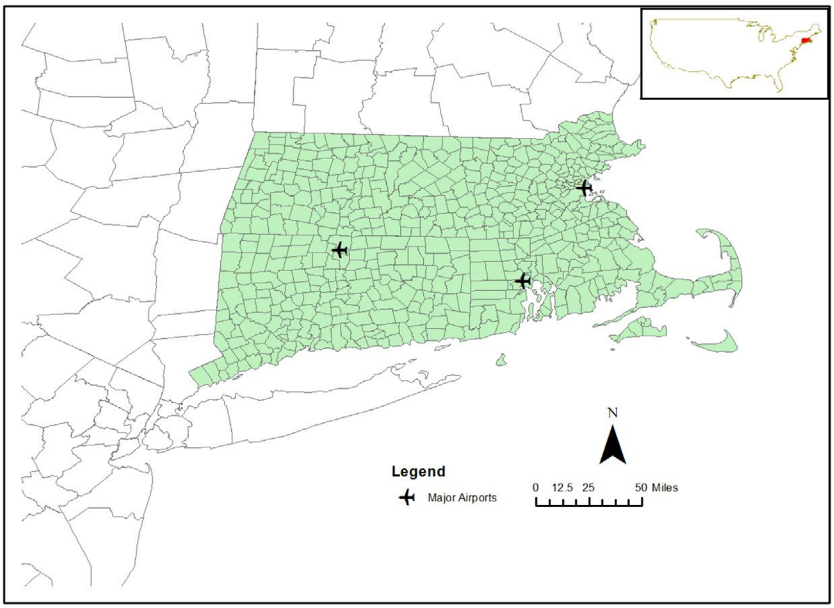

FIG. A5. Major Airports in the New England Region.
[Color figure can be viewed at wileyonlinelibrary.com]
Notes: Figure A5 shows major airports in Massachusetts, Connecticut, and Rhode Major airports are airports which transport more than 1,000,000 passengers a year.

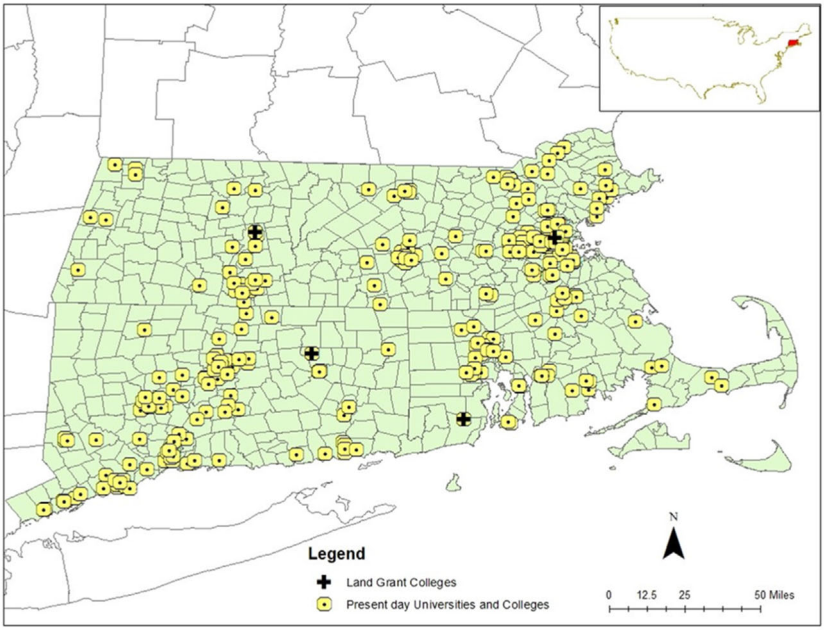

FIG. A6. Location of land grant and present-day universities.
[Color figure can be viewed at wileyonlinelibrary.com]
Notes: Figure A6 identifies the location of land grant colleges and present-day universities and colleges in Massachusetts, Connecticut, and Rhode Island.

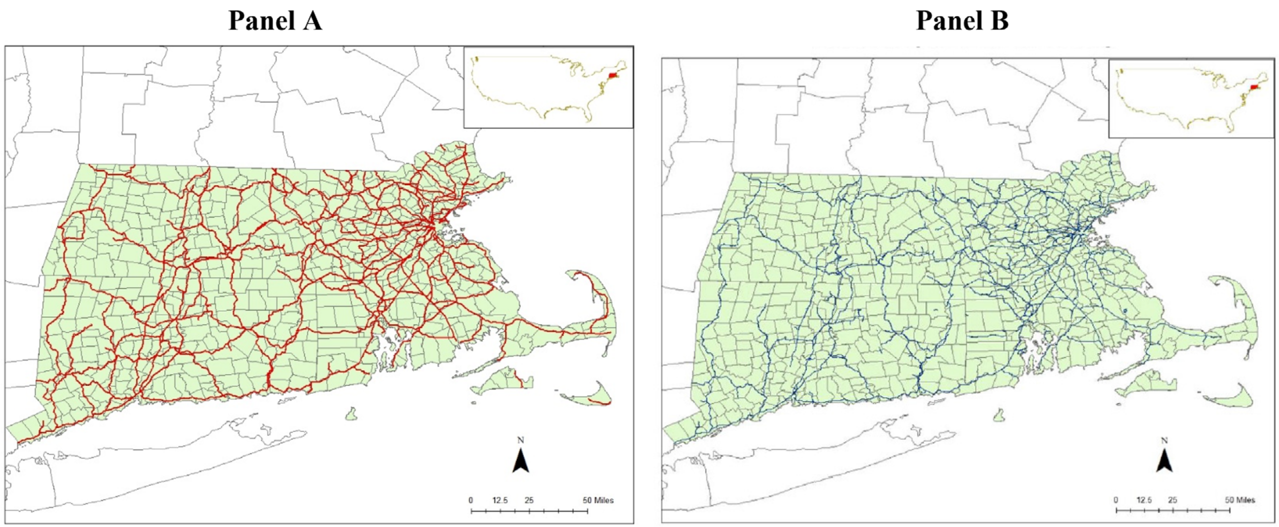

FIG. A7. New England historical and present-day railway networks.
[Color figure can be viewed at wileyonlinelibrary.com]
Notes: Figure A7 compares historical and present-day railway network lines in the states of Massachusetts, Connecticut and Rhode Island. Panel A shows historical railway network lines in the New England Region over the period 1826–1911. Panel B shows present day railway network lines in the New England Region.