Ca' Foscari University of Venice

Department of Economics

Working Paper

Licia Ferranna, Margherita Gerolimetto, and Stefano Magrini

The Evolution of Income Disparities across US Metropolitan Statistical Areas

ISSN: 1827-3580
No. 25/WP/2016

Working Papers
Department of Economics
Ca' Foscari University of Venice
No. 25/WP/2016
ISSN 1827-3580

The Evolution of Income Disparities across US Metropolitan Statistical Areas

Licia Ferranna **Margherita Gerolimetto** **Stefano Magrini**

Ca' Foscari University of Venice, Department of Economics

Abstract
The paper investigates how the spatial evolution of core-based city regions affects the dynamics of income disparities across Metropolitan Statistical Areas in the United States between 1971 and 2010. Treating initially non-metropolitan counties as part of the functional economic system for the whole time period changes the internal composition of average per capita personal income thus biasing convergence analysis. The paper analyses the dynamics of the cross-sectional distribution of per capita personal income by comparing different methods to define MSAs over time. The results show that a cluster of high income economies emerges when MSAs are allowed to evolve spatially.

Keywords
Convergence, Metropolitan Statistical Areas, Distribution Dynamics, Decentralization

JEL Codes
R12, R23, C14

Address for correspondence:
Licia Ferranna
Department of Economics
Ca' Foscari University of Venice
Cannaregio 873, Fondamenta S.Giobbe
30121 Venezia - Italy
Fax: (++39) 041 2349176
E-mail: **licia.ferranna@unive.it**

The Working Paper Series
is available only on line
(http://www.unive.it/nqcontent.cfm?a_id=86302)
For editorial correspondence, please contact:
wp.dse@unive.it

Department of Economics
Ca' Foscari University of Venice
Cannaregio 873, Fondamenta San Giobbe
30121 Venice Italy
Fax: ++39 041 2349210

1 Introduction

The paper is about the evolution of income disparities in the United States: average levels of per capita income exhibit strong and persistent differences across Metropolitan Statistical Areas. The point that we arise is that, whether US local economies are likely to walk on a convergence path depends on the very same definition of the spatial units of analysis as well as on the time-frame within which the analyses is conducted. In the US context, income differences are evident when comparing two urban areas like San Francisco, CA and Brownsville, TX, being per capita income in the former three times that in the latter. Moreover, San Francisco shows an average per capita income one third greater than Los Angeles even though it seems that the two are characterised by similar technological, legal and educational endowments (Storper, 2010).

Metropolitan Statistical Areas represent local autonomous economic systems as self-contained as possible in terms of commuting patterns. Their use in convergence analysis should be preferred over alternative administratively defined spatial units at least for two reasons (Magrini, 2004): (i) criteria to define core-based city regions are uniform across the whole US territory and (ii) their geographical extension includes both workplaces as well as residences. The latter feature avoids the emergence of nuisance spatial dependence problems (Anselin and Rey, 1991) due to a mismatch between the spatial pattern of the process under analysis and the boundaries of the observational units.

Processes of decentralisation or recentralisation of residences relative to workplaces modify the geographic extension of Metropolitan Statistical Areas over time. From the Seventies, the United States have experienced a movement of people outward core areas and a dispersion of firms throughout the metropolitan areas (OTA, 1995) even though mixed patterns have been identified when considering shorter periods (Fuguitt, 1985; Frey et al., 1993). Official statistics at metropolitan level provided by the Bureau of Economic Analysis do not consider the spatial evolution of Metropolitan Statistical Areas as they rely on the most recent delineation realised by the Office of Management and Budget which is fitted backward as if core-based city regions had had the same geographic extension from the beginning to the end of the time series. This method of defining Metropolitan Statistical Areas over time, the *fixed area* approach, may deliver different statistics than those resulting from the *floating area* approach that accounts for the evolution of the geographical extension of the functional economic region (Fuguitt et al., 1988; Nucci and Long, 1995).

The sensitivity of statistical findings to the size and shape of spatial units is known as the Modifiable Areal Unit Problem (MAUP) as firstly introduced by Gehlke and Biehl (1934) and further developed by Openshaw (1977). Recently, Briant et al. (2010) assess the magnitude of the bias with an application to French data by comparing administrative, functional, and random spatial units and concluding that "the MAUP induces much smaller distortions than economic misspecification" (page 25). In this regard, Menon (2012) underlines how their findings depend on the fact that French political geography presents some peculiarities that prevent their conclusions to be generalized; moreover, the statistical significance of the results is not testable because the random counterfactual is based on a single iteration. Whether the geographical extension of the spatial units of analysis is considered as fixed or changeable over time is likely to deliver different results when analysing convergence patterns.

The issue of regional convergence in the US has been extensively studied but authors have achieved contradictory results. It is possible to categorize the findings in accordance to the approaches that have been used. The regression approach, usually associated to the notion of beta convergence (Barro et al., 1991; Barro and Sala-i Martin, 2003), entails cross-section data analyses which tend to report evidence of unconditional convergence (Rey and Montouri, 1999; Higgins et al., 2006; Checherita, 2009). Different results are obtained when relying on panel data (Lall and Yilmaz, 2001; Shioji, 2001) and time series (Carvalho and Harvey, 2005; Holmes et al., 2013) methods. Both procedures often describe a tendency towards conditional convergence, i.e. spatial units converge in different clubs. Ambiguous results are also found when using the Distribution Dynamics approach (Quah, 1993a,b, 1996b,a, 1997) with which some authors such as Hammond and Thompson (2002) and Johnson (2000) found evidences of strong convergence while others are in favour of polarization (Wang, 2004; DiCecio and Gascon, 2010). Yamamoto (2007) analyses the evolution of income differences at various spatial scales, ranging from counties to multi-state regions, to demonstrate that smaller scales experience higher spatial income disparities, especially in the last few decades.

The present research contributes upon the literature on convergence dynamics by assessing the sensitivity of the findings to a dynamic version of Modifiable Areal Unit Problem, i.e. the one deriving from the spatial evolution of Metropolitan Statistical Areas over time. In order to achieve our aim, we construct two time series (from 1969 to 2012) on per capita personal income at metropolitan scale. The former follows the *fixed area* approach and aggregates counties into Metropolitan Statistical Areas by keeping constant over time the end-of-period delineation; the latter employs the *floating area* approach and allows spatial units to change shape and size over time. Subsequently, we compare the Distribution Dynamics results deriving from the use of the two series. The findings indicate that both the inter and the intra-distributional dynamics may be significantly different and some patterns cannot be identified by ignoring the spatial evolution of core-based city regions. As a matter of fact, both in the long-run and in the short-term the *floating area* approach reveals the presence of a cluster of high-income economies.

The paper is structured as follow. Section 2 explains in details the concept of Metropolitan Statistical Areas in the US, how they are defined, the patterns of spatial evolution detected in the last fifty years and the methods employed to account for them; Section 3 describes the methodological framework and in Section 4 we present the empirical analysis. Section 5 concludes.

2 Metropolitan Statistical Areas' Definition

The Metropolitan Statistical Area is defined as a core region containing a large population nucleus, together with surrounding communities that present a high degree of social and economic integration with the core (Bureau of the Census, 1994). The concept of metropolitan area arose at the beginning of the Twentieth Century with the observation that the physical extent of large urban agglomerations rarely coincided with official city limits. Especially in those areas later identified as *Industrial Districts*[1], suburban territories often overflew city boundaries: already in 1846, population in Boston appeared to be small without considering neighbouring towns not included in the city charter but actual component parts of the city (Hayward, 1846).

In 1950, the Federal Bureau of the Budget (later renamed Office of Management and Budget, OMB) established the Standard Metropolitan Area[2] to identify the functional zone of economic and social integration around a central place. In order to maximize the availability of statistical data, the Federal Bureau of the Budget decided that metropolitan boundaries have to match the borders of the *counties*, i.e. the smallest administratively defined territorial units covering the whole nation[3]. A number of drawbacks arise when using the county as the building block for the construction of Metropolitan Statistical Areas, first of all because they often contain a large rural component; therefore, the real extent of the functional zone tends to be overstated, especially in some Western states (Parr, 2007)[4]. For example, in California, the geographi-

[1] The definition of *Industrial Districts* - later renamed *Metropolitan Districts* - provided by the Bureau of the Census in 1905, may be considered as a first attempt to identify functional economic areas for the cities of New York, Boston, Chicago and St. Louis.

[2] The collective term used for Federal metropolitan areas have varies over time, beginning with Standard Metropolitan Areas (SMA) in 1950, Standard Metropolitan Statistical Areas (SMSA) in 1960 to Metropolitan Statistical Areas (MSA) in 1980.

[3] An exception is New England, where subcounty units - cities and towns- have a wide range of statistics available.

[4]Alternative approaches have been suggested to define a system of settlements areas that

cal extent of San Bernardino and Riverside counties is around 70,000 Km^2 but most of the area is in unoccupied desert. Nonetheless, the two counties constitutes the Riverside-San Bernardino MSA which belongs also to the Greater Los Angeles' region that combines adjacent metropolitan statistical areas.

Generally speaking, a Metropolitan Statistical Area is a county or group of counties that either contain at least one city of minimum 50,000 inhabitants or has to be *metropolitan* in character and *integrated* with the central city. The former is the *central county*, the latter qualifies as the *outlying county*. In order to be *metropolitan* in character, a county has to: 1) either contain (or employ) 10,000 non-agricultural workers, or contain (or employ) at least one tenth as many non-agricultural workers as the central county, or contain more than 50% of the population in minor civil divisions that have a population density of at least 150 inhabitants per square mile (240 inhabitants per Km^2); and 2) have a labour force that is at least 75% non-agricultural. Furthermore, a county may be considered as *integrated* if: 1) more than 15% of the workers residing in the outlying county work in the central one, or 2) 25% of the workers employed in the outlying county live in the central one. Hence, the social and economic integration of surrounding residential areas with the employment core is defined in terms of daily commuting rather than, for example, city's trade area.

Despite many adjustments in terminology and criteria, the general concept of Metropolitan Statistical Areas that official delineations are supposed to represent has remained unchanged. According to the Geographic Areas Reference Manual provided by the Bureau of the Census, "Most of the changes in the standards have been minor and have not reflected significant deviations from the concepts underlying the standards used for the 1950 Census" (Bureau of the Census, 1994, page 13-5). The argument may ensure scholars about the coherence in the use of Metropolitan Statistical Areas for the whole period ranging from the middle of the century to the present days.

---

could overcome these limitations, see for example Berry et al. (1969) and Adams et al. (1999).

Spatial Evolution of Metropolitan Statistical Areas

The geographic extension of the area that corresponds to a local and autonomous economic system modifies over time as settlements evolve and commuting systems change. In the United States, the spatial distribution of jobs and residential areas have followed mixed patterns over time. Since the post-war period, the tendency has been for people to move outward beyond the suburbs and for firms to disperse throughout the metropolitan area (OTA, 1995). Despite the general decentralizing behaviour, some differences have been observed from one decade to the next. In particular, the 1970s have witnessed the so-called *non-metropolitan turnaround* (Fuguitt, 1985) when non-metropolitan areas were found to be growing faster than metropolitan counterparts. The trend reversed in the Eighties with the *new urban revival* (Frey et al., 1993) which lasted until the end of the decade as a new *rural rebound* commenced (Johnson and Beale, 1995). By looking at job growth by sectors, Gordon et al. (1998) define the 1980s as an anomaly when accounting for Frostbelt - Sunbelt differences: even in that period there have been steady decentralization, often beyond the suburbs into rural areas. Carlino and Chatterjee (2002) observe that most of the empirical studies analysing long-term urban evolution concentrate on population size while overlooking population density. By focusing on the latter aspect, it is possible to identify a pattern of employment and population *deconcentration* from the Fifties to the Nineties: the urban employment (population) share of relatively dense metropolitan areas has declined while that of less dense metropolitan areas has increased. Moreover, the authors argue that the shift in employment (population) to metropolitan areas of lower density, has been accompanied by a *decentralization* process from dense areas toward the less dense ones within individual MSAs.

The official delineations of Metropolitan Statistical Areas change over time following the patterns of residential decentralization as well as the spatial evolution of the local economic system. The Office of Management and Budget (OMB) updates the official boundaries every decade, as new information warrants. In particular, some counties that were initially classified as non-metro change status over time, being incorporated into existing MSAs. For example, in 1960 the St. Louis MSA consisted of seven counties; by 2005 the St. Louis MSA had expanded to encompass seventeen counties. At each revision, the statistics for the metro and non-metro portion of every state are recalculated by the Bureau of Economic Analysis (BEA) to reflect the most recent county classification. When the Office of Mangement and Budget adds a new Metropolitan Statistical Area, the Bureau of Economic Analysis creates a time series for it even though it may not have had any urban area at the beginning of the period. Similarly, when the OMB changes the definition of a statistical area, the BEA recreates the time series for that area, using the same definition (the new one) for every year in the time series. For example, when OMB first defined the Gainesville, FL MSA, it consisted of the single county of Alachua. The current definition of the Gainesville, FL MSA, consists of Alachua and Gilchrist counties. BEAs' estimates of personal income and employment for the Gainesville, FL MSA also consist of the same two counties every year from 1969 to the present day.

The use of recalculated time series may be a source of measurement error when dealing with long-term demographic and economic statistics. One bias applies to MSAs that grew rapidly in population and geographic size over the analysed time range. For these MSAs, the current boundaries overstates land area and population for early years of the sample. In particular, the convergence analysis between metropolitan areas may be affected by the way in which spatial units of analysis are defined. Drennan et al. (2004) argues that results may be biased in favour of convergence because those counties that acquire the metropolitan status later in time with respect to the beginning of the period of analysis tend to be poorer than counties originally part of the MSA. In general, convergence results may differ according to the method adopted for defining the boundaries of MSAs over a long period of time because autonomous economic regions follow distinct spatial patterns. For MSAs that have experienced a substantial geographic expansion, the adoption of the most recent definition for the entire time series may introduce measurement errors both overstating population size and understating income levels.

The implications of measurement errors related to metropolitan areal boundaries definition have been considered only by few scholars, especially in the field of population studies. Fuguitt et al. (1988) evaluate different methods to describe the process of metropolitan - nonmetropolitan population change and show how alternative county designations affect the results, even though the *turnaround* of the 1970s and the subsequent return to metropolitan concentration in the 1980s do not arise as a consequence of the way counties are designated as metropolitan or not. In particular, the authors compare the metropolitan-nonmetropolitan growth differentials for each decade from 1950 to 1990 by adopting two methods. The *floating area* approach uses the universe of metro counties at the beginning (or end) of each decade while the *fixed area* classify the same counties as metropolitan throughout the series. The former implies that the universe of counties designated metropolitan changes for each decade (Hall and Hay, 1980) according to the OMB's defintions. The results show how population growth rates for metropolitan counties are systematically higher when using a floating area approach according to which initially nonmetropolitan counties are excluded from the metropolitan growth rate computation.

Acknowledging the ambiguities introduced by using constant boundaries, Nucci and Long (1995) study the spatial and demographic dynamics of metro and nonmetro territory in the US by adopting a spatial components-of-change approach that identifies the separate contribution of core areas spreading outward and newer areas being formed and expanding. Population change is firstly analysed in Metropolitan Statistical Areas in existence at the beginning of the period and then neighbouring counties are added to the urban fringe as the OMB's updates the delineations. Ehrlich and Gyourko (2000) document changes in the population size distribution of metropolitan areas from 1910 to

1995. In order to overcome arbitrariness in the delineations of metropolitan areas, they investigate a variety of possible definitions, ranging from *floating area* approach to *fixed area* classification based on the initial or final year. The results are robust across metropolitan areas definitions and show that, following the Second World War, the top decile in the distribution of metropolitan areas by size loses population in favour of the next largest decile.

Gottlieb (2006) conducts a study on *decentralization* and *deconcentration* in the United States in the period 1970-2000. The author suggests to assess the evolution of the American settlement system over time by looking at the distribution of population or employment across types of metropolitan areas as defined at each decennial census. By adopting the *floating area* method, it is possible to avoid the measurement error and to report the metropolitan status of different places as accurate as possible. On the other way round, it would not be possible to identify individual preferences for counties that are at the bottom of the urban hierarchy but that gradually move up as people and jobs migrate there. In contrast, Carlino and Chatterjee (2002) highlight the importance of reducing this kind of measurement error when using density to measure employment deconcentration, arguing that any negative correlation between growth and employment density may spuriously be enhanced by the erroneous underestimation of density at the beginning of the time series. In order to alleviate the problem, the authors use metropolitan areas boundaries from a single year but adopt a middle-period definition.

In the empirical section, we evaluate the implications of alternative definitions of Metropolitan Statistical Areas for the convergence analysis. Hence, we borrow the methods developed by the demographic literature that accounts for the spatial evolution of MSAs and apply them to the Distribution Dynamics approach firstly discussed by Quah (1993a) in order to assess the evolution of cross-sectional distribution of per capita income across MSAs. In particular, we compare convergence results obtained by using either the *floating area* or the *fixed area* approach as introduced by Fuguitt et al. (1988).

3 Distribution Dynamics Approach

We analyse convergence using the Distribution Dynamics approach (Quah, 1993a,b, 1996a,b, 1997), in which the evolution of the cross-sectional distribution of per capita income is examined directly, using stochastic kernels to describe both the change in the distribution's external shape and the intra-distribution dynamics.

Consider two random variables, Y_t and Y_{t+s}, which represent per capita income of a group on N economies observed, respectively, at time t and $t+s$. Express the variables in relative terms with respect to the group average and consider the cross-sectional distributions $F(Y_t)$ and $F(Y_{t+s})$. Then, assume that a density exists for each of the two distributions, i.e. $f(Y_t)$ and $f(Y_{t+s})$. Finally, suppose that the law of motion between time t and $t+s$ can be modelled as a first order process; therefore, the density at time $t+s$ is given by:

$$f\left(Y_{t+s}\right) = \int_{-\infty}^{\infty} f\left(Y_{t+s}|Y_t\right)\, f\left(Y_t\right)\, dY_t \tag{1}$$

where $f(Y_{t+s}|Y_t)$ is a stochastic kernel mapping the density at time t into the density at time $t+s$ which describes where points in $f(Y_t)$ end up in $f(Y_{t+s})$. An estimate of this operator provides two sets of information: on the one hand, we observe how the external shape of the distribution evolves over time; on the other hand, the intra-distribution dynamics emerges as economies moves from one part of the distribution to another. Hence, convergence may be studied either by looking directly at the plot of the conditional density estimate or by analysing the ergodic distribution. In the latter case, we assume that the first order process is Markovian time homogeneous and we compare the shape of the initial distribution with the stationary one that is defined as the limit of $f(Y_{t+s})$ as $s \to \infty$.

A common method to estimate the stochastic kernel in Equation (1) is through the kernel estimator. Given a sample $(Y_{1,t}, Y_{1,t+s}, \ldots, Y_{j,t}, Y_{j,t+s}, \ldots, Y_{n,t}, Y_{n,t+s})$ of size n, the kernel density estimator of Y_{t+s} conditional on Y_t is:

$$\hat{f}(Y_{t+s}|Y_t) = \sum_{j=1}^{n} w_j(Y_t) K_b(Y_{t+s} - Y_{j,t+s}) \tag{2}$$

where

$$w_j(Y_t) = \frac{K_a(Y_t - Y_{j,t})}{\sum_{j=1}^{n} K_a(Y_t - Y_{j,t})} \tag{3}$$

with a and b bandwidths controlling the degree of smoothness and K a kernel function.

Notwithstanding the large use in the empirical literature, the estimator in Equation (2) might have poor bias properties. These limitations have been highlighted and discussed by Hyndman et al. (1996), who proposes to estimate the mean function implicit in the kernel density estimator by using an estimator with better properties than the Nadarya-Watson estimator, such as the local linear estimator (Loader, 1999). In the empirical section of the paper, we estimate the stochastic kernel with the mean bias adjustment. In particular, we employ Gaussian kernels and we fix the degree of smoothing using cross validation (Green and Silverman, 1993). Estimates of the mean functions are obtained via a local linear estimator with nearest-neighbour bandwidth.

Following Gerolimetto and Magrini (2014), we use smoothed time series in the Distribution Dynamics analysis. In particular, we apply the Hodrick Prescott (HP) filter[5] (Hodrick and Prescott, 1997) to get rid of short term fluctuations connected to the business cycle that are likely to bias the results, as shown by Magrini et al. (2015). Let's assume that regional per capita income time series are the sum of two elements: a trend y_t^g and a cycle y_t^c for

[5] We rely on HP filter because of its simplicity and widespread use. For criticism see, for example, Canova (1998) and Gomez (2001). Gerolimetto and Magrini (2014) show that the choice of the band-pass filter does not significantly affect the convergence results.

$t = 1, \ldots, T$. The estimate of the trend component via the HP filter is obtained by minimizing the following problem with respect to y_t^g:

$$\sum_{t=1}^{T} [(y_t - y_t^g)^2 + \lambda(y_t^g - 2y_{t-1}^g + y_{t-2}^g)^2)] \tag{4}$$

for a given value of λ, which is the parameter that controls the degree of smoothness of the estimated trend and the shape of the cyclical swings: as λ increases, the estimated trend component approaches a linear function.

Which value should be assigned to the λ parameter is a highly debated issue, discussed for example in Harvey and Trimbur (2008) and Ravn and Uhlig (2002)[6]. As suggested by Kaiser and Maravall (1999), the choice of the degree of smoothness should reflect the specific interests of the researcher. By drawing on Gerolimetto and Magrini (2014), we assume $\lambda = 40$ for annual data; the value is computed according to the rule proposed by Ravn and Uhlig (2002) who calculate the HP parameter from the value for quarterly data by multiplying it by 4^{-4}. In particular, the HP parameter for quarterly data is set equal to 10000, a value computed following Gomez (2001) who derives λ based on the cut-out frequency which depend on the period of a complete business cycle and determine the frequency threshold for a swing to be assigned to the cycle. Moreover, Gerolimetto and Magrini (2014) adjust the proportion between average and cut-out cycles in order to take into consideration the fact that, for a given average duration at the national level, the average duration at the state (and at the MSAs) level may be longer. This derives from the fact that the US cycle is a weighted average of the states' cycles. Finally, we ignore estimates at the sample endpoints because they tend to be close to the observations thus failing to remove the cycle component from the trend (Baxter and King, 1999).

[6] Hodrick and Prescott (1997) interpret λ as the ratio between the variance of the cyclical component and the variance of the second difference of the growth component. Without estimating the variances, the authors suggest to use $\lambda = 100$ as a rule of thumb for annual data.

4 Empirical Analysis

We study convergence patterns across 161 US Metropolitan Statistical Areas in terms of real per capita personal income net of current transfer receipts. We prefer to employ personal income rather than GDP[7] because the industrial reclassification from the Standard Industrial Classification (SIC) to the North American Industry Classification System (NAICS) prevents the availability of GDP data before 2001. The whole period of analysis ranges from 1969 to 2012. The main source of the data is the Bureau of Economic Analysis, which provides the historical series for population, personal income and personal current transfer receipts. We remove from aggregate personal income the amount of transfers and we compute per capita average dividing by population. Thereafter, we transform the series in real terms by using Consumer Price Index provided by the Bureau of Labour Statistics.

Convergence analysis is evaluated on two different time series. The first one considers per capita personal income as provided directly at the metropolitan level by the Bureau of Economic Analysis that compute the values following the *constant area* approach. In particular, BEA considers the last definition of Metropolitan Statistical Areas released by the Office of Management and Budget and fits it backwards up to 1969. The second series is computed according to the *floating area* approach. Data are drawn from BEA at the county level and then aggregated at the metropolitan scale according to the definitions provided every decade by the OMB. In the dataset, delineations change in 1970, 1980, 1990 and 2000.

We evaluate the sensitivity of the convergence results to the Modifiable

[7]Personal Income is computed as GDP minus: capital depreciation, corporate profits with inventory valuation and capital consumption adjustments, contributions for government social insurance, domestic net interest and miscellaneous payments on assets, net business current transfer payments, current surplus of government enterprises, and undistributed wage accruals; plus: net income from assets abroad, personal income receipts on assets, and personal current transfer receipts.

Areal Unit Problem that emerges from different criteria according to which data are aggregated at the metropolitan level both in the long as well as in the short run. In both cases, the series on per capita personal income are smoothed by means of the HP filter with the λ parameter set to 40 for eliminating cyclical fluctuations. In order to minimize the inaccuracies in the estimation of the end-points, we reduce the series employed in the convergence analysis to a time period ranging from 1971 to 2010.

The Distribution Dynamics approach is employed in the empirical analysis. The output consists of a set of figures: a three-dimensional plot of the estimated stochastic kernel, a Highest Density Region (HDR) plot as proposed by Hyndman (1996) and a plot comparing the initial distribution with the ergodic. The first figure allows to analyse convergence directly form the shape of the three-dimensional plot of the stochastic kernel: a concentration of the graph along the main diagonal describes the situation in which the elements of the cross-sectional distribution do not change position from the initial to the final year, i.e. the evolution of per capita personal income is characterised by a high degree of persistence. On the other way round, a concentration of the graph around the value one of the final dimension axis and parallel to the initial dimension axis means that the set of economies are converging; the formation of different modes indicates polarization. The HDR plot represents conditional densities for a specific value in the initial year dimension by vertical stripes which are different in colours: the darker the greater the highest density region percentage. Finally, we compare the two ergodic distributions resulting from the *constant area* and the *floating area* approach in a unique plot, where the stationary distributions are evaluated on a common grid. Given the two empirical Cumulative Density Functions, a Cramér - Von Mises test (Anderson, 1962) is performed to evaluate if they come from the same underlying distribution.

Figures 1 and 2 present the results for the whole period, i.e. 1971-2010. We present in Figure 1 the three-dimensional plot of the estimated stochastic kernel (left), the High Density Region plot (middle) and the comparison between the initial (dashed) and the ergodic (solid) distribution (right) for the *fixed area* approach (above) and the *floating area* approach (below). Moreover, the comparison between the two ergodics resulting from the application of the two methods is represented in Figure 2: the *fixed area* stationary distribution is the dotted one, the *floating area* the dashed. Finally, we report the results of the Cramér - Von Mises (CVM) test and two indexes of dispersion, i.e. the Inter Quantile Range (IQR) and the Coefficient of Variation (CV) measured both for the ergodic distributions and for the difference between the initial and the ergodic distributions.

Figure 1 show a tendency to divergence regardless of the method used to compute per capita personal income time series at the metropolitan level. Nonetheless, some differences exist between the two approaches. In particular, the *floating area* approach highlights the presence of a thicker right tail while the rest of the graph is concentrated around a peak below the average. As a matter of fact, the three-dimensional and the HDR plots describe a situation of persistence and moderate convergence up to average relative income values that changes into divergence as we approach higher levels. On the other hand, *fixed area* approach shows a flatter stationary distribution and does not emphasis the emergence of a high income levels cluster. Despite some common features, the Cramér - Von Mises (CVM) test indicates that the two ergodics in Figure 2 do not come from the same underlying distribution, i.e. they are significantly different. Despite this, the dispersion indexes are quite similar across the two approaches.

As highlighted by Gerolimetto and Magrini (2014), if we identify a tendency towards convergence or divergence over a long time period, nothing may be said about cross-sectional evolution patterns over shorter sub-periods. As a matter of fact, a tendency towards convergence over several decades may hide a period of divergence lasting just for some years. For this reason, and in order to understand if results differ according to the approach used even in relatively shorter time periods, we perform the Distribution Dynamics for three sub-periods of different lengths, i.e. 1971-1978, 1979-1985, 1986-2010. Figures 3 and 4 refer to the former time span. The plots present a number of interesting features: first of all, per capita personal income have persistently remained in the position where they started; secondly, most of the economies are concentrated on an unique mode that is set around the average value; finally, the alternative use of the *floating area* rather than *fixed area* approach does not deliver any significantly different result. In fact, Figure 4 and the Cramér - Von Mises test show that the two ergodic distributions are almost the same. The results indicate that, despite the *floating* and the *fixed* series of per capita personal income differ especially in these initial years, the average internal composition of MSAs remains almost unaltered.

Things change a lot when moving to the subsequent period. The pattern of convergence across economies identified for the time span 1971-1978 reverses and a clear tendency towards divergence emerges between 1979 and 1984 (Figures 5 and 6). In general, the ergodic distributions show the emergence of two peaks, respectively, at the top and at the bottom of the distribution. The existence of a high per capita income club of economies is more evident when using the *floating area* approach, as it was for the tighter right tail in the long run. High numbers are associated with both the Coefficient of Variation and the Inter Quantile Range, thus indicating substantially dispersed ergodic distributions. Moreover, also the Dispersion Indexes evaluated for the difference between the initial and ergodic distributions underline how we are moving from a situation of relative equality to a more unequal state.

Finally, let us discuss the findings for the last sub-period which ranges between 1985 to 2010 (Figures 7 and 8). In this case, it is clear that using either the *floating area* approach or the *fixed area* method delivers completely different results. By adopting the latter, it seem that most of the economies are converging around a mode that departs only marginally from the average peaking on a value slightly lower than one. In fact, the three-dimensional plot as well as the High Density Region plot (Figure 7, above) reflects a situation of persistence for most of the values and the graph is concentrated on the main diagonal with the exception of the initially higher income levels, which evolve by increasing the gap with respect to the mean. On the other hand, Figure 7 (below) represents a situation in which economies diverge when moving from the initial to the final year. If the evolution follows a time homogeneous Markov process, two distinct modes arise, as shown by the stationary distribution. The High Density Region plot offers additional insights. Poorest economies move above the main diagonal and form a cluster with the other economies slightly below the average, which instead remain where they started. The same happens for the elements above the average: those relatively closer to the mean value stay where they were at the beginning of the period, the highest-income economies form a club at the top of the distribution. Obviously, by looking at Figure 8, it is easy to see even by eye that the two ergodic distributions are totally different, and the Cramér - Von Mises test statistically demonstrates it. As expected, the Indexes of Dispersion evaluated for the difference between the initial distribution and the stationary one show how, when using the *fixed area* approach, the distributions changes only marginally while a discrepancy up to 0.42 (IQR) is experienced when adopting the *floating area* approach. For the ergodic distribution estimated using the dataset relative to the *floating area* method, the same measure of dispersion arrives at 0.64, thus highlighting the character of divergence between MSAs.

In sum, the use of a *floating area* approach to build per capita personal income time series for Metropolitan Statistical Areas highlights some features of the convergence dynamics otherwise impossible to detect. In particular, both in the long-run and in the short-run, the presence of a cluster of rich economies is identified, either in the form of a mode or as a long and tight right tail. On the contrary, the internal composition of MSAs in terms of per capita personal income that derive from the application of the *fixed area* approach may bias the convergence results hiding the existence of a second peak.

Figure 1: *Fixed Area* (above), *Floating Area* (below): 1971-2010

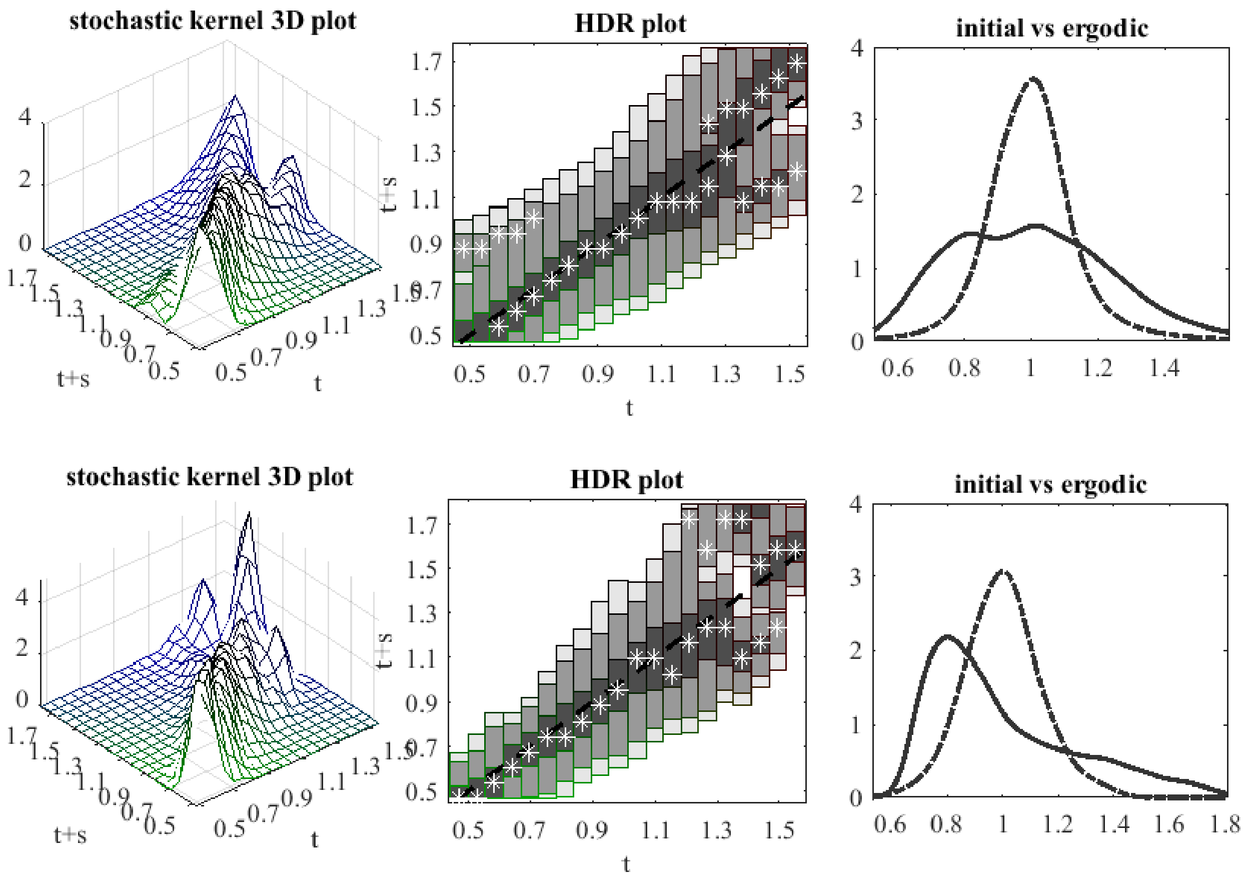
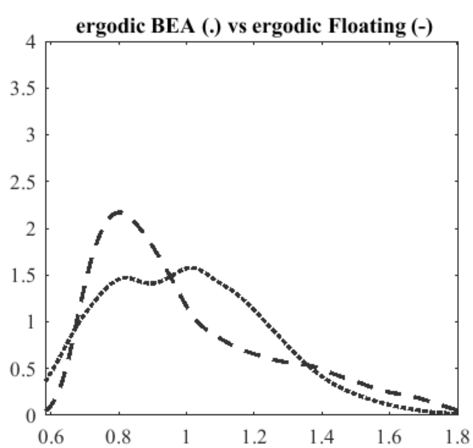


Figure 2: Ergodic Distributions: 1971-2010



	Statistics	p-value
CVM Test	15.0403	0.000
Δ from t	**CV**	**IQR**
Fixed	0.1073	0.1757
Floating	0.1270	0.1190
Ergodic	**CV**	**IQR**
Fixed	0.2562	0.3613
Floating	0.2772	0.3123

Figure 3: *Fixed Area* (above), *Floating Area* (below): 1971-1978

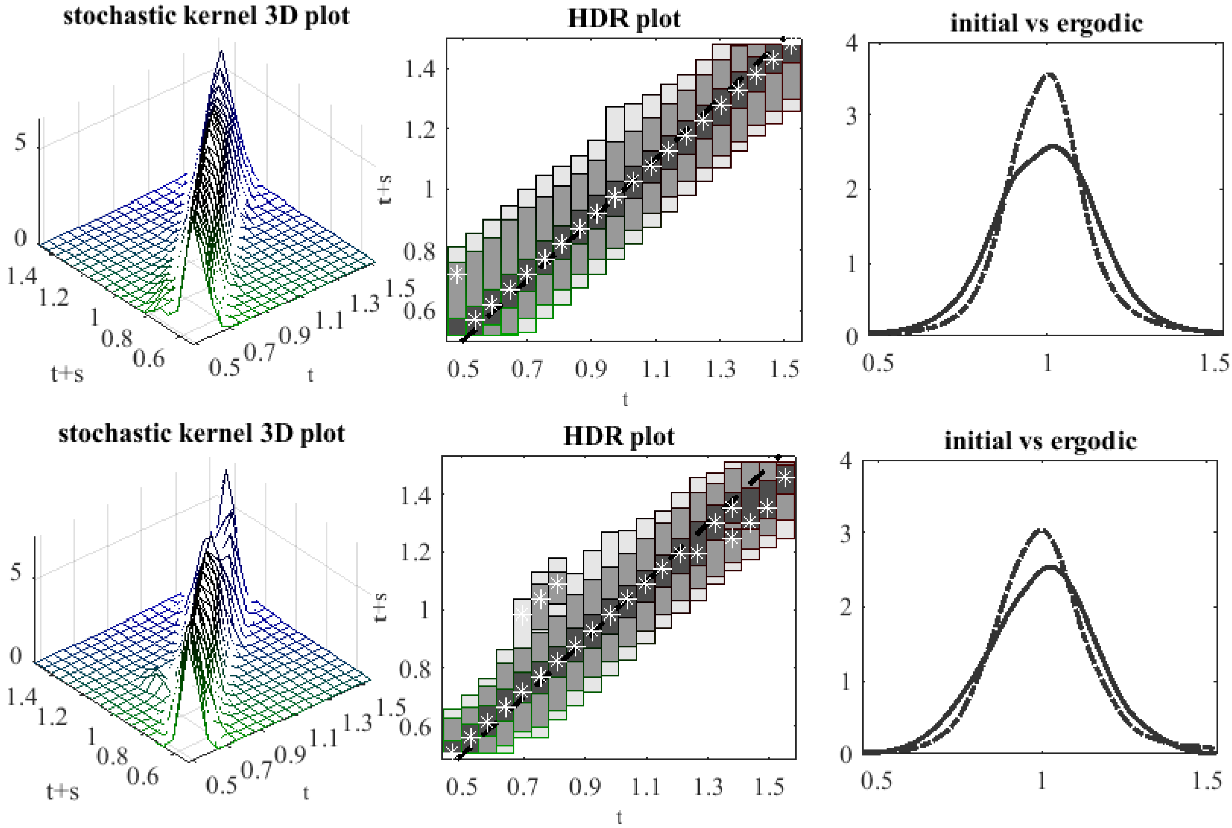
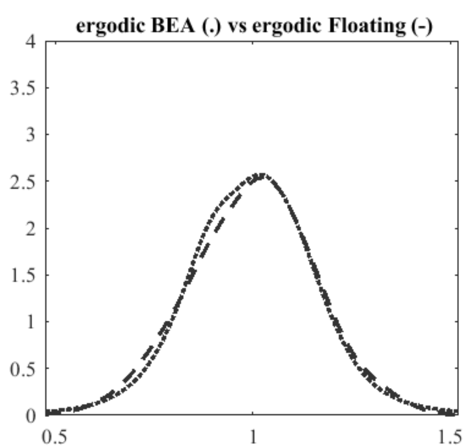


Figure 4: Ergodic Distributions: 1971-1978



	Statistics	**p-value**
CVM Test	0.1573	0.3742
Δ from t	**CV**	**IQR**
Fixed	0.0238	0.0584
Floating	0.0111	0.0435
Ergodic	**CV**	**IQR**
Fixed	0.1789	0.2455
Floating	0.1746	0.2406

Figure 5: *Fixed Area* (above), *Floating Area* (below): 1979-1984

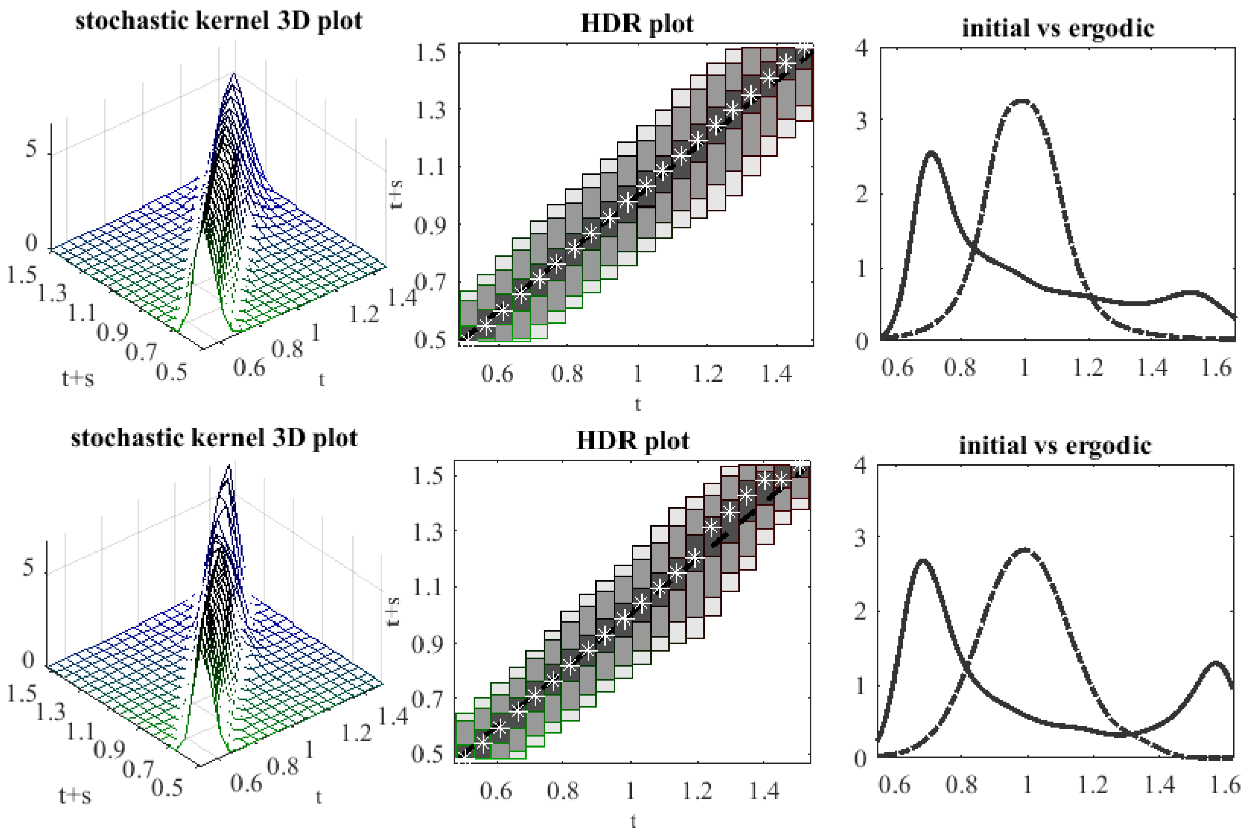
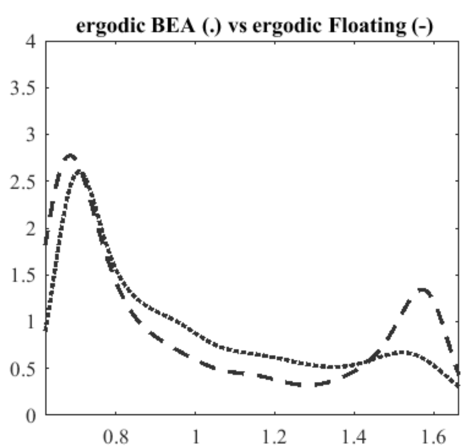


Figure 6: Ergodic Distributions: 1979-1984



	Statistics	**p-value**
CVM Test	2.2464	0.0000
Δ from t	**CV**	**IQR**
Fixed	0.1777	0.2693
Floating	0.2107	0.4165
Ergodic	**CV**	**IQR**
Fixed	0.3245	0.4608
Floating	0.3648	0.6229

Figure 7: *Fixed Area* (above), *Floating Area* (below): 1985-2010

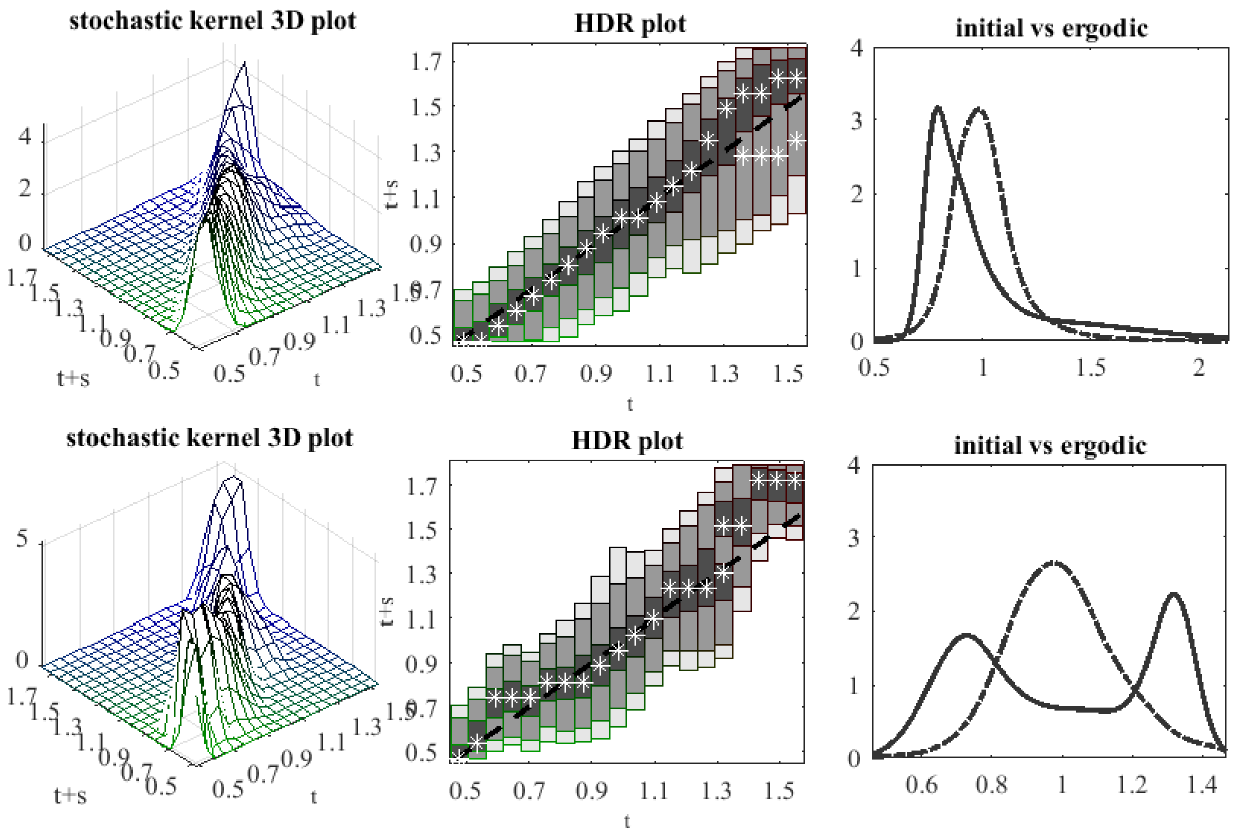
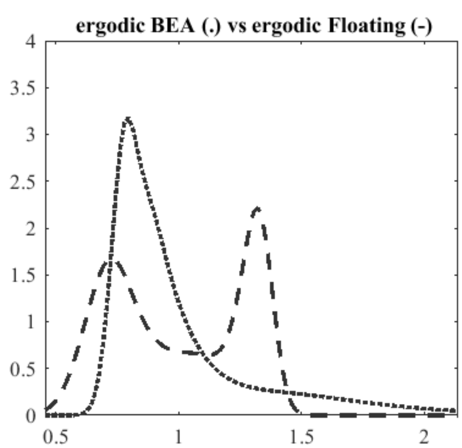


Figure 8: Ergodic Distributions: 1985-2010



	Statistics	**p-value**
CVM Test	118.5684	0.0000
Δ from t	**CV**	**IQR**
Fixed	0.1529	0.0022
Floating	0.1202	0.4193
Ergodic	**CV**	**IQR**
Fixed	0.3154	0.2075
Floating	0.2907	0.6422

5 Conclusions

The paper provides a contribution over the empirical literature on per capita income levels evolution across Metropolitan Statistical Areas in the United States. The use of core-based city regions as spatial units of analysis in convergence studies have a number of advantages over administratively defined ones: they are as self contained as possible in terms of commuting patterns; therefore, local statistics are not biased for the fact that income levels are measured at workplaces and population at residences. Nonetheless, over a long time period such as the one analysed in the empirical section, Metropolitan Statistical Areas change their size and shape. By ignoring their spatial evolution, we are introducing a bias on the statistics about population, mean income levels and, thus, average per capita incomes which may be interpreted as a Modifiable Areal Unit Problem in dynamic terms. Results of the convergence analysis change when the geographic extent of the MSAs is allowed to vary over time and disclose the presence of a cluster of economies characterised by high income levels.

References

Adams, J. S., B. J. VanDrasek, and E. G. Phillips (1999). Metropolitan area definition in the United States. *Urban Geography 20*(8), 695–726.

Anderson, T. W. (1962). On the distribution of the two-sample Cramer - Von Mises criterion. *The Annals of Mathematical Statistics*, 1148–1159.

Anselin, L. and S. Rey (1991). Properties of tests for spatial dependence in linear regression models. *Geographical analysis 23*(2), 112–131.

Barro, R. J. and X. Sala-i Martin (2003). Economic growth. *MIT Press Books 1*.

Barro, R. J., X. Sala-i Martin, O. J. Blanchard, and R. E. Hall (1991). Convergence across states and regions. *Brookings papers on economic activity*, 107–182.

Baxter, M. and R. G. King (1999). Measuring business cycles: approximate band-pass filters for economic time series. *Review of Economics and Statistics 81*(4), 575–593.

Berry, B. J. L., P. G. Goheen, and H. Goldstein (1969). *Metropolitan area definition: A re-evaluation of concept and statistical practice*, Volume 28. US Bureau of the Census.

Briant, A., P.-P. Combes, and M. Lafourcade (2010). Dots to boxes: Do the size and shape of spatial units jeopardize economic geography estimations? *Journal of Urban Economics 67*(3), 287–302.

Bureau of the Census, U. S. (1994). Geographic Areas Reference Manual. *Washington, DC. Wruck, KarenH*.

Canova, F. (1998). Detrending and business cycle facts. *Journal of Monetary Economics 41*(3), 475–512.

Carlino, G. and S. Chatterjee (2002). Employment deconcentration: a new perspective on America's postwar urban evolution. *Journal of Regional Science 42*(3), 445–475.

Carvalho, V. M. and A. C. Harvey (2005). Growth, cycles and convergence in US regional time series. *International Journal of Forecasting 21*(4), 667–686.

Checherita, C. D. (2009). Variations on economic convergence: The case of the United States. *Papers in Regional Science 88*(2), 259–278.

DiCecio, R. and C. S. Gascon (2010). Income convergence in the United States: a tale of migration and urbanization. *The Annals of Regional Science 45*(2), 365–377.

Drennan, M. P., J. Lobo, and D. Strumsky (2004). Unit root tests of sigma income convergence across US metropolitan areas. *Journal of Economic Geography 4*(5), 583–595.

Ehrlich, S. and J. Gyourko (2000). Changes in the scale and size distribution of US metropolitan areas during the twentieth century. *Urban Studies 37*(7), 1063–1077.

Frey, W. H. et al. (1993). The new urban revival in the United States. *Urban Studies 30*, 741–741.

Fuguitt, G. V. (1985). The nonmetropolitan population turnaround. *Annual Review of Sociology*, 259–280.

Fuguitt, G. V., T. B. Heaton, and D. T. Lichter (1988). Monitoring the metropolitanization process. *Demography 25*(1), 115–128.

Gehlke, C. E. and K. Biehl (1934). Certain effects of grouping upon the size of the correlation coefficient in census tract material. *Journal of the American Statistical Association 29*(185A), 169–170.

Gerolimetto, M. and S. Magrini (2014). A novel look at long-run convergence dynamics in the United States. *International Regional Science Review*.

Gomez, V. (2001). The use of butterworth filters for trend and cycle estimation in economic time series. *Journal of Business & Economic Statistics 19*(3), 365–373.

Gordon, P., H. W. Richardson, and G. Yu (1998). Metropolitan and nonmetropolitan employment trends in the US: recent evidence and implications. *Urban Studies 35*(7), 1037–1057.

Gottlieb, P. D. (2006). “Running down the up escalator”: A revisionist perspective on decentralization and deconcentration in the United States, 1970-2000. *International Regional Science Review 29*(2), 135–158.

Green, P. J. and B. W. Silverman (1993). *Nonparametric regression and generalized linear models: a roughness penalty approach*. CRC Press.

Hall, P. G. and D. Hay (1980). *Growth centres in the European urban system*. Univ of California Press.

Hammond, G. W. and E. Thompson (2002). Mobility and modality trends in US state personal income. *Regional Studies 36*(4), 375–387.

Harvey, A. and T. Trimbur (2008). Trend estimation and the Hodrick-Prescott filter. *Journal of the Japan Statistical Society 38*(1), 41–49.

Hayward, J. (1846). The New England Gazetteer. *Boston: 48th edition*.

Higgins, M. J., D. Levy, and A. T. Young (2006). Growth and convergence across the United States: evidence from county-level data. *The Review of Economics and Statistics 88*(4), 671–681.

Hodrick, R. J. and E. C. Prescott (1997). Postwar US business cycles: an empirical investigation. *Journal of Money, credit, and Banking*, 1–16.

Holmes, M. J., J. Otero, and T. Panagiotidis (2013). A note on the extent of US regional income convergence. *Macroeconomic Dynamics*, 1–21.

Hyndman, R. J. (1996). Computing and graphing highest density regions. *The American Statistician 50*(2), 120–126.

Hyndman, R. J., D. M. Bashtannyk, and G. K. Grunwald (1996). Estimating and visualizing conditional densities. *Journal of Computational and Graphical Statistics 5*(4), 315–336.

Johnson, K. M. and C. L. Beale (1995). The rural rebound revisited. *American Demographics 17*(7), 46–54.

Johnson, P. A. (2000). A nonparametric analysis of income convergence across the US states. *Economics Letters 69*(2), 219–223.

Kaiser, R. and A. Maravall (1999). Estimation of the business cycle: A modified Hodrick-Prescott filter. *Spanish Economic Review 1*(2), 175–206.

Lall, S. V. and S. Yilmaz (2001). Regional economic convergence: Do policy instruments make a difference? *The Annals of Regional Science 35*(1), 153–166.

Loader, C. (1999). Local regression and likelihood. *NY Springer-Verlag*.

Magrini, S. (2004). Regional (di) convergence. *Handbook of regional and urban economics 4*, 2741–2796.

Magrini, S., M. Gerolimetto, and H. Engin Duran (2015). Regional convergence and aggregate business cycle in the United States. *Regional Studies 49*(2), 251–272.

Menon, C. (2012). The bright side of MAUP: defining new measures of industrial agglomeration. *Papers in Regional Science 91*(1), 3–28.

Nucci, A. and L. Long (1995). Spatial and demographic dynamics of metropolitan and nonmetropolitan territory in the United States. *International Journal of Population Geography 1*(2), 165–181.

Openshaw, S. (1977). A geographical solution to scale and aggregation problems in region-building, partitioning and spatial modelling. *Transactions of the institute of british geographers*, 459–472.

OTA (1995). The Technological Reshaping of Metropolitan Areas. *Washington, DC: US Governemnt Printing Office*.

Parr, J. B. (2007). Spatial definitions of the city: four perspectives. *Urban Studies 44*(2), 381–392.

Quah, D. (1993a). Empirical cross-section dynamics in economic growth. *European Economic Review 37*(2), 426–434.

Quah, D. (1993b). Galton's fallacy and tests of the convergence hypothesis. *The Scandinavian Journal of Economics*, 427–443.

Quah, D. T. (1996a). Convergence empirics across economies with (some) capital mobility. *Journal of Economic Growth 1*(1), 95–124.

Quah, D. T. (1996b). Empirics for economic growth and convergence. *European economic review 40*(6), 1353–1375.

Quah, D. T. (1997). Empirics for growth and distribution: stratification, polarization, and convergence clubs. *Journal of economic growth 2*(1), 27–59.

Ravn, M. O. and H. Uhlig (2002). On adjusting the Hodrick-Prescott filter for the frequency of observations. *Review of Economics and Statistics 84*(2), 371–376.

Rey, S. J. and B. D. Montouri (1999). US regional income convergence: a spatial econometric perspective. *Regional studies 33*(2), 143–156.

Shioji, E. (2001). Public capital and economic growth: a convergence approach. *Journal of Economic Growth 6*(3), 205–227.

Storper, M. (2010). Why does a city grow? Specialisation, human capital or institutions? *Urban Studies*.

Wang, Y. (2004). A nonparametric analysis of the personal income distribution across the provinces and states in the US and Canada. *Regional and Sectoral Economic Studies 4*(1).

Yamamoto, D. (2007). Scales of regional income disparities in the USA, 1955–2003. *Journal of Economic Geography*.