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Spatial Economic Disparities across the United States

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Abstract

The thesis deals with spatial economic disparities in the United States. The first chapter, "The Evolution of Income Disparities across US Metropolitan Statistical Areas", 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 nonmetropolitan 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. The second chapter, "Urban governance Structure and Wage Disparities among US Metropolitan Areas", analyses the determinants of spatial wage disparities in the US context for the period 1980-2000. Agglomeration benefits are estimated based on city productivity premia which are computed after controlling for the skills distribution among metropolitan areas as well as industry fixed effects. The drivers of productivity differentials that are taken into consideration are the size of the local economy, the spatial interactions among local autonomous economic systems and the structure of urban governance as well as the policy responses to the fragmentation issue. A metropolitan area with ten percentage more administrative units than another of the same size, experiences wages that are between 2,0% and 3,0% lower. The presence of a voluntary governance body is found to mitigate the problem of fragmentation only marginally, while the existence of special purpose districts have a negative impact on regional productivity. The implementation of a metropolitan government with a regional tax system is expected to increase productivity by around 6%. Finally, the third chapter, "The effect of immigration on convergence dynamics in the US", studies the impact of immigration on the dynamics of the cross-sectional distribution of GSP per capita and per worker. To achieve this aim, we combine different approaches: on the one hand, we establish via Instrumental Variable estimation the effect of the inflow of foreign-born workers on output per worker, employment and population; on the other hand, using the Distribution Dynamics approach, we reconstruct the consequences of migration flows on convergence dynamics across US states.

Table of contents

List of figures

List of tables

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Chapter 1

The Evolution of Income Disparities across US Metropolitan Statistical Areas

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 [1].

[1]Co-authored chapter with Margherita Gerolimetto and Stefano Magrini

1.1 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 analysis 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).

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 and Sala-i Martin, 1991, 2004), entails cross-section data analyses which tend to report evidence of unconditional convergence (Checherita, 2009; Higgins et al., 2006; Rey and Montouri, 1999). 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, 1996a,b, 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 (DiCecio and Gascon, 2010; Wang et al., 2004). Yamamoto (2008) 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.

In regional studies, the choice of the spatial unit of analysis requires specific attention (Cheshire and Carbonaro, 1995; Cheshire and Magrini, 2000; Cheshire and Hay, 1989; Magrini, 1999). 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, 2004a): (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.

Nuisance spatial dependence problems may create misleading statistics for per capita output, which is the most common dependent variable used in convergence analysis. As a matter of fact, output is measured at workplace while population is measured in the place of residence. Hence, output will be correctly represented only in the case in which boundaries of the statistical unit of analysis identify regions which are as self contained as possible in terms of commuting. The choice of Metropolitan Statistical Areas as spatial unit of analysis meets the need because they are relatively independent local economic systems in which the impacts of an economic shock is almost contained and homogeneously distributed.

Processes of decentralisation or recentralisation of residences relative to workplaces as well as of economic activities 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 (Frey et al., 1993; Fuguitt, 1985). 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 use of Metropolitan Statistical Areas may be a useful strategy for minimising nuisance spatial dependence problems in a static framework but it does not completely solve the problem in dynamic terms. As the patterns of centralization or decentralisation evolve over time, the boundaries of Metropolitan Statistical Areas modify accordingly and per capita output will be misrepresented unless the boundaries of the statistical unit of analysis coincide with the local autonomous economic system at each point in time. For example, let's consider the case of a metropolitan area that expands decade after decade. At the beginning of the period that we consider for the convergence analysis, the outer territories were excluded from the local economic and labour system. Over time, economic activity expansion as well as residential decentralization have pushed the borders of the metropolitan area into rural areas, which have become part of the autonomous local economic system. In this case, by neglecting the evolution in the boundaries of the Metropolitan Statistical Area, per capita output may be underestimated because statistics are computed by including also that portion of territories which used to be rural. In fact, Table 1.1 shows how, on average, per capita personal income is initially lower when adopting a *floating area* approach to define Metropolitan Statistical Areas. Nonetheless, US Metropolitan Statistical Areas have followed distinct patterns of decentralization of economic activities or residences: for example, Atlanta, GA have expanded over time from five counties in 1960 to twenty in 2000 while Boston, MA, has remained almost spatially fixed over time. The present study shows that the use of a *floating area* approach to construct the statistics related to Metropolitan Statistical Areas is useful to detect patterns of (di)convergence which may not be identified when relying on a *constant area* method.

Table 1.1: PCPI by Metropolitan Areas Definition

	1970		**1990**		**2010**	
	Floating	*Constant*	*Floating*	*Constant*	*Floating*	*Constant*
Mean	9658.12	9407.47	12531.11	12309.74	14071.58	13861.71
Median	9649.58	9366.22	12317.61	12129.43	13614.38	13714.23
Min	4444.30	4444.30	5631.77	5640.37	6754.61	6652.11
Max	15330.74	14339.95	20914.66	19404.79	24203.50	24398.74

In general, 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 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.

1.2 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*[2], 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[3] 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[4]. 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)[5]. For example, in California, the geographical 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

[2] 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.

[3] 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.

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

[5]Alternative approaches have been suggested to define a system of settlements areas that could overcome these limitations, see for example Berry et al. (1969) and Adams et al. (1999).

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.

1.2.1 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 postwar 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) argue 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 non-metro 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).

1.3 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, $\bar{y}_t$ and $\bar{y}_{t+s}$, which represent the level of per capita income of a Metropolitan Statistical Area relative to the cross sectional average 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 $F\bar{y}(_t)$ and $F(\bar{y}_{t+s})$. Then, assume that a density exists for each of the two distributions, i.e. $f(\bar{y}_t)$ and $f(\bar{y}_{t+s})$. 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:

$$f\left(\bar{y}_{t+s}\right) = \int_{-\infty}^{\infty} f\left(\bar{y}_{t+s}|\bar{y}_t\right)\, f\left(\bar{y}_t\right)\, d\bar{y}_t \tag{1.1}$$

where $f(\bar{y}_{t+s}|\bar{y}_t)$ is a stochastic kernel mapping the density at time t into the density at time $t+s$ which describes where points in $f(\bar{y}_t)$ end up in $f(\bar{y}_{t+s})$. 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 move 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 $f(\bar{y}_{t+s})$ as $s \to \infty$.

A common method to estimate the stochastic kernel in Equation (1.1) is through the kernel estimator. Given a sample $(\bar{y}_{1,t}, \bar{y}_{1,t+s}, \ldots, \bar{y}_{j,t}, \bar{y}_{j,t+s}, \ldots, \bar{y}_{n,t}, \bar{y}_{n,t+s})$ of size n, the kernel density estimator of $\bar{y}_{t+s}$ conditional on $\bar{y}_t$ is:

$$\hat{f}(\bar{y}_{t+s}|\bar{y}_t) = \sum_{j=1}^{n} w_j(\bar{y}_t) K_b(\bar{y}_{t+s} - \bar{y}_{j,t+s}) \tag{1.2}$$

where

$$w_j(\bar{y}_t) = \frac{K_a(\bar{y}_t - \bar{y}_{j,t})}{\sum_{j=1}^{n} K_a(\bar{y}_t - \bar{y}_{j,t})} \tag{1.3}$$

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 (1.2) 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).

Important implications for the analysis could also arise from its spatial dimension. Gerolimetto and Magrini (2016) note that the estimate of $f\left(\bar{y}_{t+s}|\bar{y}_t\right)$ is in fact an autoregression and emphasize that the asymptotic properties of the adopted smoother are usually based on the assumption that the error terms are zero mean and uncorrelated. However, in the analysis of economic convergence across spatial units, the involved variables are usually characterized by spatial dependence. Within the distribution dynamics approach the issue is typically tackled by adopting a spatial filtering technique before proceeding with the estimates. In the present paper, we adopt the strategy developed by Gerolimetto and Magrini (2016) and therefore enrich the estimate of the conditional density through an estimate of the mean function that, in addition to Hyndman et al.s' original suggestion, allows also for spatial dependence. A more detailed discussion about the spatial nonparametric estimator may be found in Section 3.3.3.

Following Gerolimetto and Magrini (2014), we use smoothed time series in the Distribution Dynamics analysis. In particular, we apply the Hodrick Prescott (HP) filter[6] (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 $t = 1, \ldots, T$. The estimate of the trend component via the HP filter is obtained by minimizing the following problem with respect to y_t^g:

$$\sum_{t=1}^{T}[(y_t - y_t^g)^2 + \lambda(y_t^g - 2y_{t-1}^g + y_{t-2}^g)^2)] \tag{1.4}$$

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)[7]. 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

[6] 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.

[7] 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.

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).

1.4 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[8] 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 *fixed 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.

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[8] 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.

We evaluate the sensitivity of the convergence results to the Modifiable 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 *fixed 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.

Before proceeding to the analysis of the figures, a note on the estimate of the stochastic kernel. The estimate is carried out using the procedure developed by Gerolimetto and Magrini (2016) in which the mean function of the conditional density is obtained using a spatial nonparametric estimator. The results of the Moran's I test on the residuals of the estimate of $f\left(\bar{y}_{t+s}|\bar{y}_t\right)$ that substantiate this choice are reported in Table 1.2. It is clear from this table that all residuals obtained using the traditional nonparametric smoother in the estimate of $f\left(\bar{y}_{t+s}|\bar{y}_t\right)$ display spatial dependence to a significative extent. In contrast, essentially no signs of spatial dependence are found in the residuals from the estimates produced using the spatial nonparametric estimator.

Table 1.2: Moran's I p-values on Data and Nonparametric Regression Residuals

	Fixed	*Floating*
Data		
1971	0.000	0.000
1978	0.000	0.000
1979	0.000	0.000
1984	0.000	0.000
1985	0.000	0.000
2010	0.000	0.001
Mean function estimate - nonparametric regression residuals		
1971-2010	0.000	0.000
1971-1978	0.000	0.000
1979-1984	0.000	0.000
1985-2010	0.000	0.006
Mean function estimate - spatial nonparametric regression residuals		
1971-2010	0.691	0.312
1971-1978	0.993	0.923
1979-1984	0.985	0.990
1985-2010	0.969	0.984

Note: Moran's I test carried out using a 10-nearest neighbor spatial weight matrix.

Figures 1.1 and 1.2 present the results for the whole period, i.e. 1971-2010. We present in Figure 1.1 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 1.2: 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 1.1 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 1.2 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 1.3 and 1.4 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 1.4 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 1.5 and 1.6). 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 1.7 and 1.8). In this case, using either the *floating area* approach or the *fixed area* method does not deliver 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 1.7, 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 1.7 (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, a thicker right tail arises, as shown by the stationary distribution. The High Density Region plot offers additional insights. Poorest economies tend to 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. By looking at Figure 1.8, it is not easy to see by eye whether the two ergodic distributions are totally different, but the Cramér - Von Mises test statistically rejects the null hypothesis of coincide of the two distributions at 2% significance level.

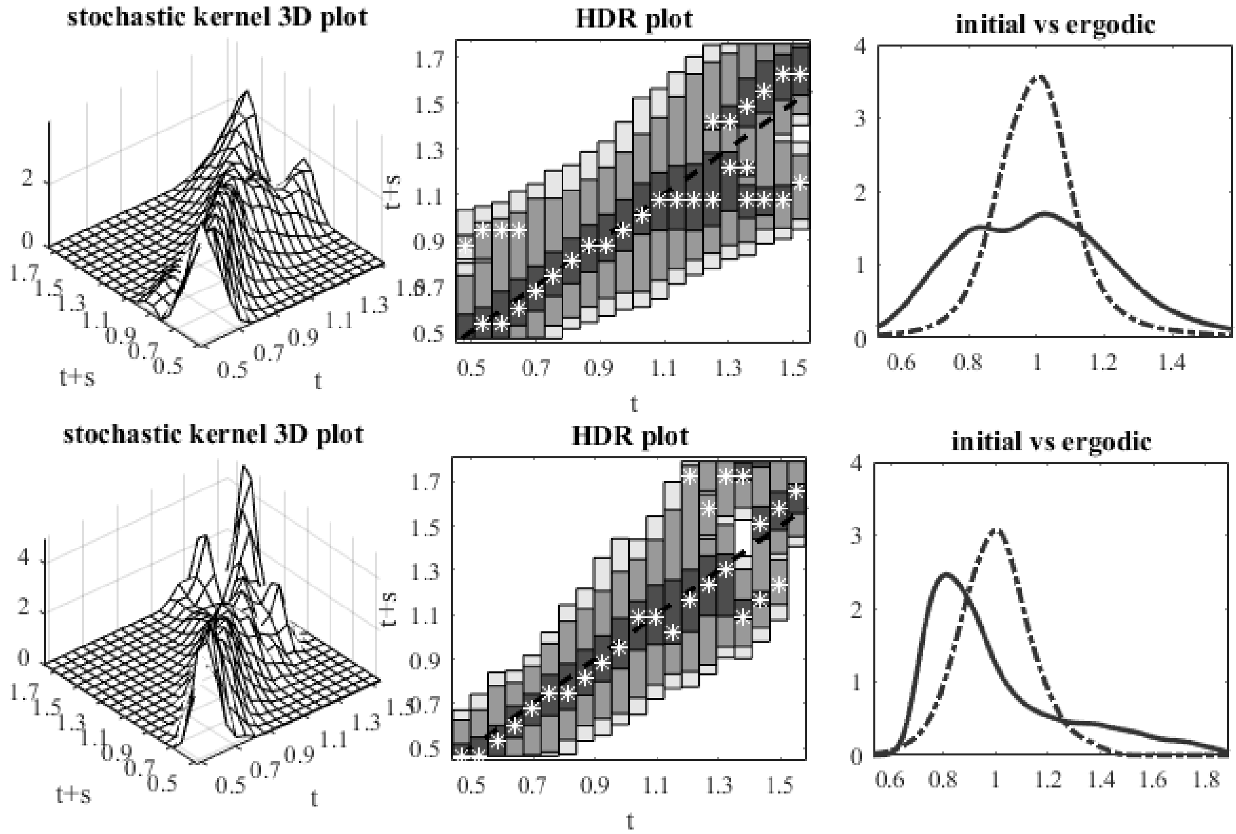
In sum, the use of a *floating area* approach to build per capita personal income time series for Metropolitan Statistical Areas highlights some features of the convergence dynamics otherwise impossible to detect. In particular, both in the long-run and in the short-run, the presence of a cluster of 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.

1.5 Conclusions

The paper provides a contribution to 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 in 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.

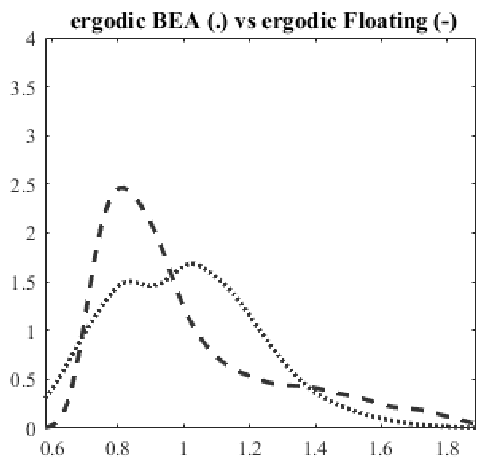
By adopting a *floating area* approach we are excluding the rural component from the computation of the statistics related to both population and economic output. As a matter of fact, Metropolitan Statistical Areas that have expanded over time are likely to present values of per capita output lower than the correct one at the beginning of the period of analysis. The distortion of the statistics may produce misleading results by affecting both the cross-sectional distribution of per capita income as well as its dynamics over time. Our findings are in line with Drennan et al. (2004) who argue 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. As a matter of fact, the use of recalculated time series may be a source of measurement error when dealing with long-term demographic and economic statistics. For MSAs that grew rapidly in population and geographic size over the analysed time range, the current boundaries overstates land area and population for early years of the sample. Hence, the convergence analysis between metropolitan areas may be affected by the way in which spatial units of analysis are defined.

Figure 1.1: *Fixed Area* (above), *Floating Area* (below): 1971-2010



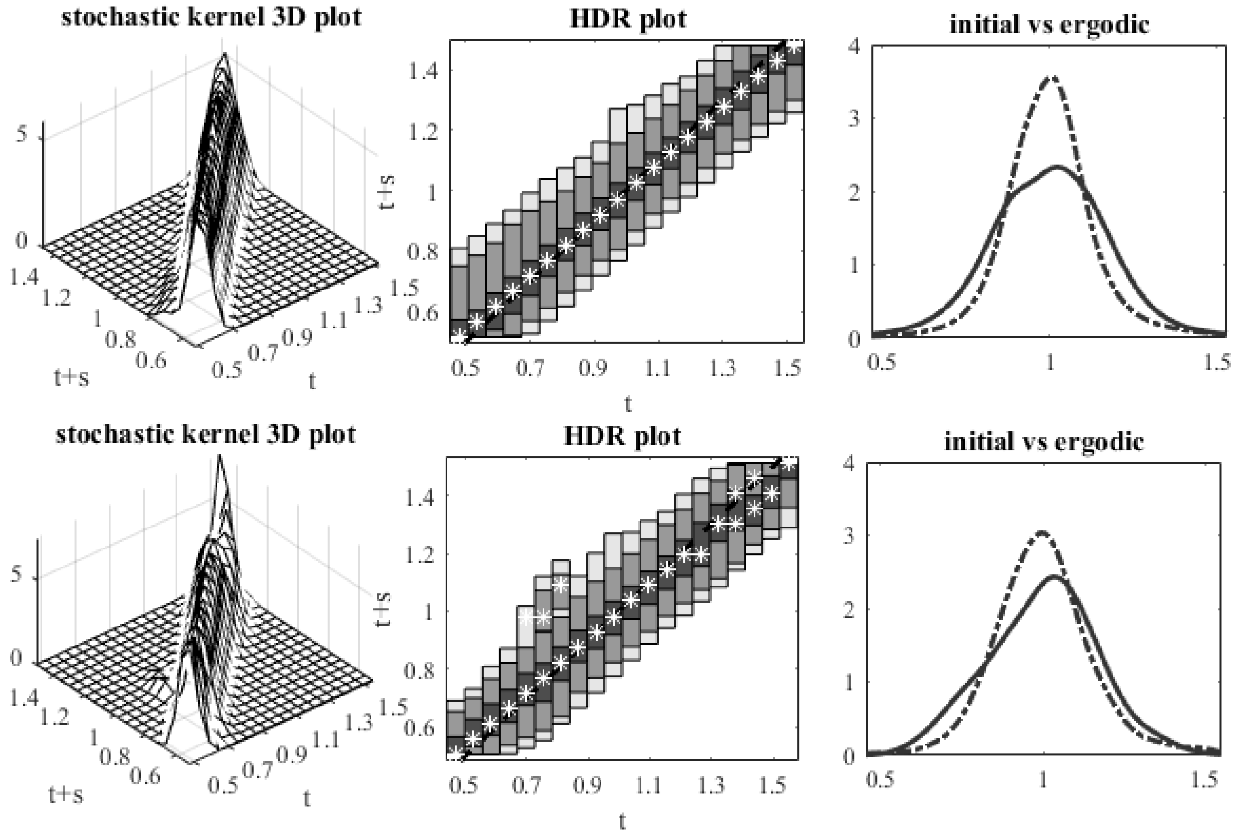
Notes: Estimates use an adaptive bandwidth (span = 0.7) based on a cross-validation minimization in the initial year dimension, a cross-validation minimization bandwidth in the final year dimension and a Gaussian kernel. Mean bias adjustment is obtained via the SNP (local linear) estimator with a cross-validation minimization bandwidth. In contour and highest density region (HDR) plots, the dashed line represents the main diagonal, the asterisk the modes. In the comparison between distributions, the dashed line represents the initial year and the continuous line represents the ergodic.

Figure 1.2: Ergodic Distributions: 1971-2010



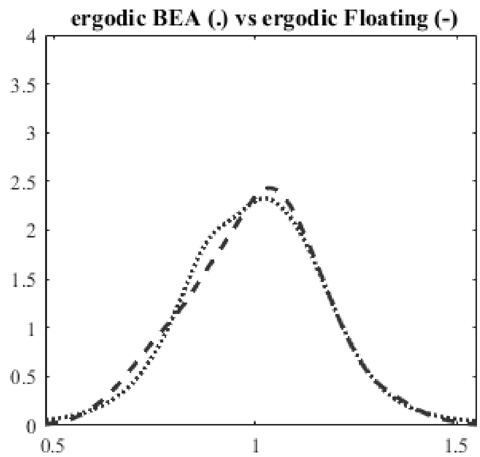
	Statistics	**p-value**
CVM Test	29.5117	0.000
Δ from t	**CV**	**IQR**
Fixed	0.0984	0.1592
Floating	0.1295	0.0678
Ergodic	**CV**	**IQR**
Fixed	0.2473	0.3448
Floating	0.2796	0.2611

Figure 1.3: *Fixed Area* (above), *Floating Area* (below): 1971-1978



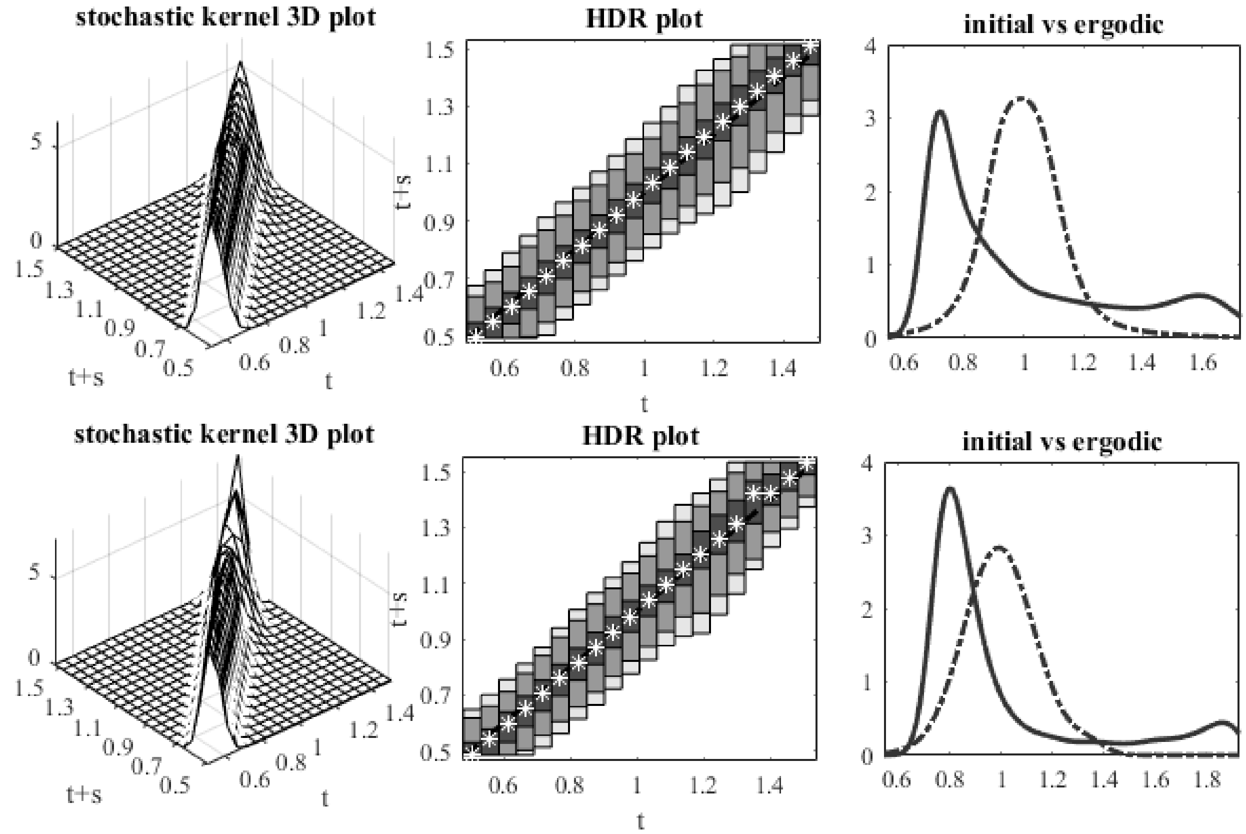
Notes: Estimates use an adaptive bandwidth (span = 0.7) based on a cross-validation minimization in the initial year dimension, a cross-validation minimization bandwidth in the final year dimension and a Gaussian kernel. Mean bias adjustment is obtained via the SNP (local linear) estimator with a cross-validation minimization bandwidth. In contour and highest density region (HDR) plots, the dashed line represents the main diagonal, the asterisk the modes. In the comparison between distributions, the dashed line represents the initial year and the continuous line represents the ergodic.

Figure 1.4: Ergodic Distributions: 1971-1978



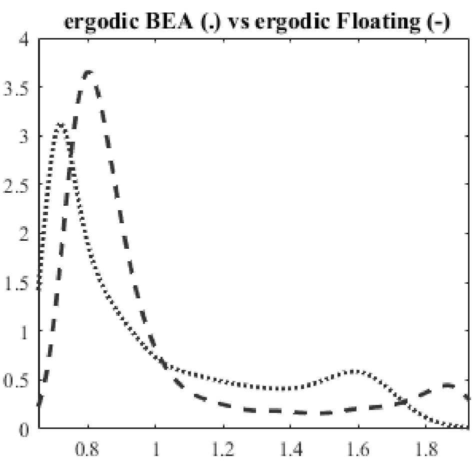
	Statistics	**p-value**
CVM Test	0.0816	0.6976
Δ from t	**CV**	**IQR**
Fixed	0.0413	0.0842
Floating	0.0243	0.0626
Ergodic	**CV**	**IQR**
Fixed	0.1964	0.2713
Floating	0.1877	0.2597

Figure 1.5: *Fixed Area* (above), *Floating Area* (below): 1979-1984



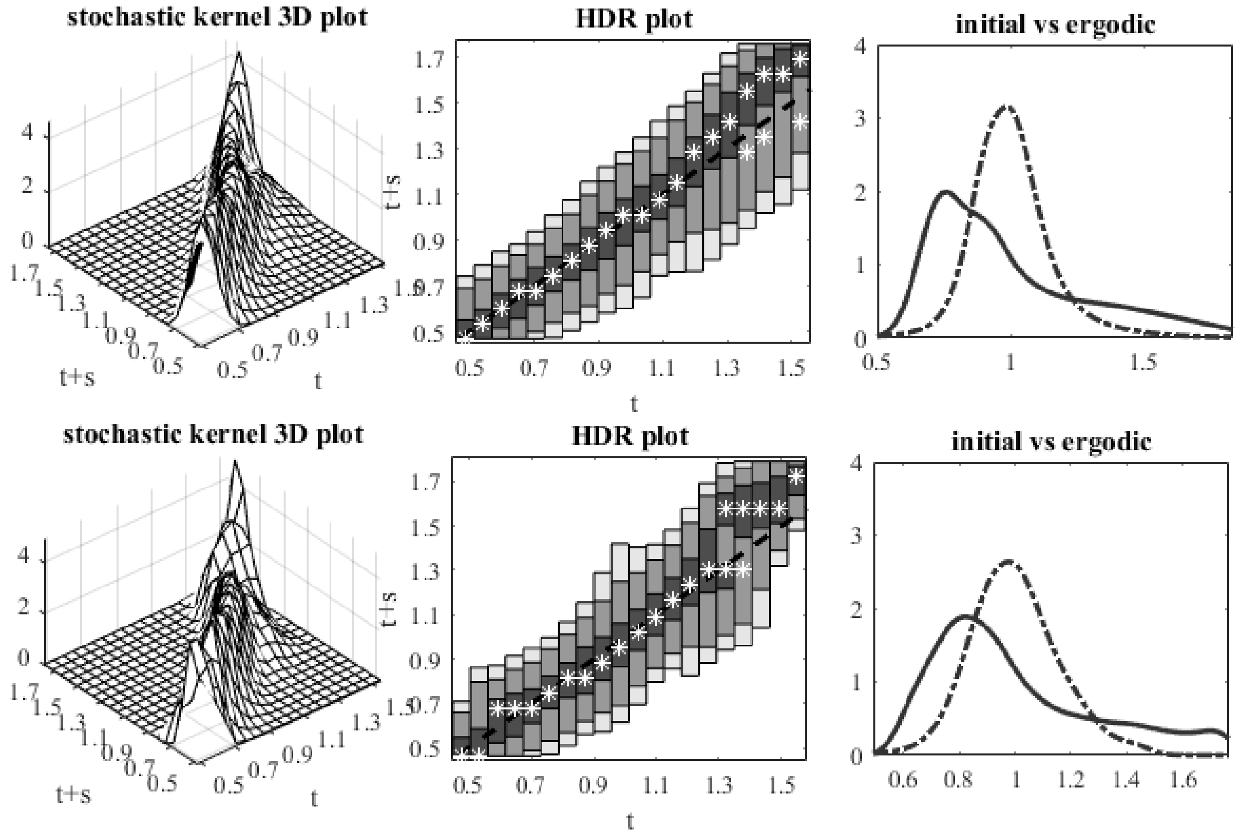
Notes: Estimates use an adaptive bandwidth (span = 0.7) based on a cross-validation minimization in the initial year dimension, a cross-validation minimization bandwidth in the final year dimension and a Gaussian kernel. Mean bias adjustment is obtained via the SNP (local linear) estimator with a cross-validation minimization bandwidth. In contour and highest density region (HDR) plots, the dashed line represents the main diagonal, the asterisk the modes. In the comparison between distributions, the dashed line represents the initial year and the continuous line represents the ergodic.

Figure 1.6: Ergodic Distributions: 1979-1984



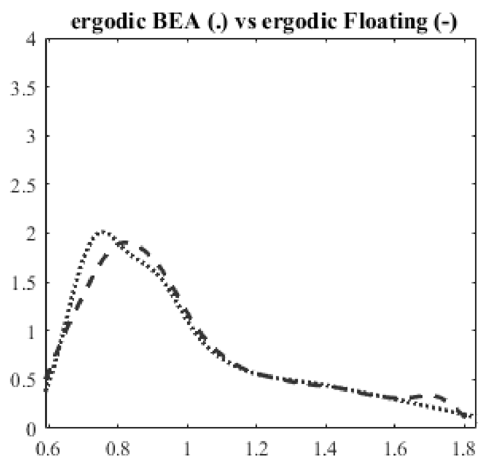
	Statistics	**p-value**
CVM Test	9.4881	0.0000
∆ from t	**CV**	**IQR**
Fixed	0.1902	0.2376
Floating	0.1972	0.0196
Ergodic	**CV**	**IQR**
Fixed	0.3370	0.4291
Floating	0.3513	0.1868

Figure 1.7: *Fixed Area* (above), *Floating Area* (below): 1985-2010



Notes: Estimates use an adaptive bandwidth (span = 0.7) based on a cross-validation minimization in the initial year dimension, a cross-validation minimization bandwidth in the final year dimension and a Gaussian kernel. Mean bias adjustment is obtained via the SNP (local linear) estimator with a cross-validation minimization bandwidth. In contour and highest density region (HDR) plots, the dashed line represents the main diagonal, the asterisk the modes. In the comparison between distributions, the dashed line represents the initial year and the continuous line represents the ergodic.

Figure 1.8: Ergodic Distributions: 1985-2010



	Statistics	**p-value**
CVM Test	1.1067	0.002
Δ from t	**CV**	**IQR**
Fixed	0.1586	0.1514
Floating	0.1442	0.1255
Ergodic	**CV**	**IQR**
Fixed	0.3211	0.3567
Floating	0.3146	0.3484

Chapter 2

Urban Governance Structure and Wage Disparities across US Metropolitan Areas

This paper analyses the determinants of spatial wage disparities in the US context for the period 1980-2000. Agglomeration benefits are estimated based on city productivity premia which are computed after controlling for the skills distribution among metropolitan areas as well as industry fixed effects. The drivers of productivity differentials that are taken into consideration are the size of the local economy, the spatial interactions among local autonomous economic systems and the structure of urban governance as well as the policy responses to the fragmentation issue. A metropolitan area with ten percentage more administrative units than another of the same size, experiences wages that are between 2.0% and 3.0% lower. The presence of a voluntary governance body is found to mitigate the problem of fragmentation only marginally, while the existence of special purpose districts have a negative impact on regional productivity. The implementation of a metropolitan government with a regional tax system is expected to increase productivity by around 6% [1].

[1]Co-authored chapter with Margherita Gerolimetto and Stefano Magrini

2.1 Introduction

In the US, the huge variability of nominal wages across metropolitan statistical areas (MSA) is a well known fact. Wage disparities are extensively documented in Moretti (2011) who argues that the difference between the 10th and the 90th percentile of the wage distribution for average high school graduates account for approximately 32%. The literature has identified a number of explanations by referring to agglomeration economies (Duranton and Puga, 2004; Marshall, 1890), locational fundamentals such as amenities (Ellison and Glaeser, 1999) and workforce skill composition (Glaeser and Resseger, 2010). Despite being often assumed as an important driver of local economic performance (Storper, 2010), the role of institutions in enhancing agglomeration benefits has tended to be overlooked by the literature. In fact, metropolitan statistical areas greatly differ both in terms of population distribution between the city centre and the outlying territories as well as for the numerousness of administrative subregions. For example, the MSA of Atlanta is a distinctive case example of metropolitan fragmentation with twenty counties and a mass transit system that does not extend far enough into the suburbs where workers live. In California, Sacramento and San Jose do not have many administrative jurisdictions but in the former metropolitan area population is twice as concentrated in the city centre.

The paucity of empirical studies is in contrast with anecdotal evidences and qualitative enquires suggesting formal structure of metropolitan governance as a channel of direct intervention for spurring local productivity (Anas, 1999; Duckett, 2012). For example, difficult coordination among local governments due to a mismatch between the boundaries of the local economic system and the administratively defined ones may obstruct infrastructure investments and effective land use planning (Ahrend et al., 2014b); moreover, a multiplicity of laws and regulations increase transaction costs for businesses that operate in multiple jurisdictions (Wolman et al., 2011). Finally, localized increasing returns may accrue from sharing facilities Puga (2010) that are more likely to be created at metropolitan scale by a club of jurisdictions. The smaller the number of participating agencies, the lower the costs of formation and maintenance of the club unless there is a dominant one that can assume a leading role (Cheshire and Gordon, 1998).

Some attempts have been made in order to mitigate the problems derived from poor metropolitan governance. In the US, these issues are addressed through two mechanisms: special purpose governments and voluntary agreements, but both solutions may have limited effectiveness. The former tend to complicate the problem by adding an other layer to the existing multiplicity of local governments (Duckett, 2012; Orfield and Gumus-Dawes, 2009); the latter may not be geographically adherent to the metropolitan area and tend to under-represent central cities in voting boards, while favouring outlying counties. Portland, OR and Minneapolis - Saint Paul, MN are two exceptions to the predominant type of metropolitan governance in the US. In fact, the former has a governance body that has the status of full local government and a leadership elected by popular vote. The latter, delivers a wide range of services and have implemented a metropolitan tax-based sharing that is welcomed by some authors (see for example Orfield, 2002; Wolman et al., 2011).

Our primary objective is to quantitatively assess the impact of different dimensions of the structure of urban governance on local productivity premia. We concentrate on the distribution of population in metropolitan areas, whether more or less concentrated in the central city, as well as on the number of administratively defined jurisdictions that divide the territory of functional economic regions. The share of inhabitants in the central jurisdiction with respect to the population of the entire metropolitan area identifies the degree of *dominance*; the level of *fragmentation* is represented by the number of municipalities that insist on the metropolitan area. Poor governance of metropolitan areas may mitigate the extent to which agglomeration enhances productivity. The analysis of the policy responses to this problem is the second objective of the paper. Governance bodies are created in order to solve coordination difficulties among local governments, but their effectiveness remains an open issue.

Empirical evidences on the role of metropolitan governance structure is rather scant. Most of the studies focus on its relationship with the rate of local economic growth (as Hammond and Tosun, 2011; Nelson and Foster, 1999; Paytas, 2001; Stansel, 2005), which is usually analysed in cross sectional growth models adopting the convergence approach pioneered by Barro (1991) and criticized as uninformative and perhaps misleading for both theoretical and empirical reasons (Cheshire and Magrini, 2009; Cheshire and Malecki, 2004). To the best of our knowledge, Ahrend et al. (2014a) is the only study that analyses the impact of fragmented governments on productivity premia in five OECD countries. Our paper follows the latter but we provide a number of original contributions to the literature. First of all, different dimensions of metropolitan governance structure enter the analysis: the number of local governments and the degree of dominance of the central city are considered as complements rather than substitutes. Other indices introduced in the literature (Grassmueck and Shields, 2010; Hamilton et al., 2004) are excluded because of both high correlation with dominance and fragmentation measures and endogeneity problems due to their computation based on local governments expenditures. Secondly, we introduce a time variability in these dimensions by letting the boundaries of the spatial units of analysis to change over time. In this way results about the difficulties deriving from poor governance of metropolitan areas are derived robustly also to the Modifiable Areal Unit Problem (Briant et al., 2010) and remain even after accounting for a state centralization component. Thirdly, we provide an evaluation of the policy responses by distinguishing between special districts, voluntary agreements that are further divided into Council of Governments (COGs) and Metropolitan Planning Organizations (MPOs), the variety of services provided by Regional Councils as well as the geographic adherence of COGs to metropolitan area. Moreover, we test the hypothesis about the beneficial impact of general purpose governments, such as the one implemented in the Twin Cities, at the metropolitan level.

From a methodological point of view, we follow the approach suggested by Combes and Gobillon (2015) consisting in a two-stages procedure where productivity premia are estimated in the first stage by using micro data and then used as dependent variable. Hypothesis about the structure of urban governance and the policy responses to the fragmentation problem are tested in the second stage where a specification including a spatial lag of the independent variable is adopted in order to take into account spatial dependence between metropolitan areas. Moreover, we propose a floating approach for the identification of metropolitan areas that takes into consideration their territorial evolution over time. By letting the spatial units of analysis free to modify the boundaries in accordance to the correspondent local autonomous economic system, it is possible to avoid biases related to the structure of urban governance. Furthermore, the analysis considers the reverse causation problem deriving from the fact that not only city productivity is affected by the density of the metropolitan area, but also the viceversa holds. In order to tackle the endogenous quantity of labour, an instrumental approach is suggested and the counter-factual for the local evolution of the population is computed from the average of national employment changes in the industrial sectors, weighted by the initial shares of local sectoral structure. Finally, the study considers the possibility that the rate of decline of agglomeration benefits is sharper than the one determined by the inverse of the distance. In order to test the hypothesis, the distance decay parameter is estimated by using a nonlinear estimation technique based on Vega and Elhorst (2015).

The analysis in this article focuses on US metropolitan areas and the period of analysis runs from 1980 to 2000. We employed microdata (IPUMS, Ruggles et al. (2015)) as well as macrodata series from the Bureau of Economic Analysis. We assess the impact of the structure of urban governance and we find that both the level of fragmentation and the degree of dominance of the central city have an effect on the rise of agglomeration externalities that is significant. In particular, a metropolitan area with ten percentage more administrative units than another of the same size, experiences wages that are between 2.0% and 3.0% lower. Moreover, a ten percentage point decrease in the share of population living in the central city is estimated to reduce productivity by a small on average but highly significant amount, that is between 0.7% and 0.8%. By nonlinearly estimating the distance decay parameter, rather than imposing it beforehand, it turns out that the rate of decline of agglomeration benefits is sharper than the one determined by the inverse of the distance. Finally, the presence of a voluntary governance body or a high number of special districts determine a lower level of productivity, meaning that they do not solve the coordination problems at the regional level. The result remains as it is even after looking in details at the services provided by the Regional Councils. Instead, the presence of a general purpose metropolitan government is expected to increase local productivity by about 6%.

The rest of the paper is structured as follows. Section 2 describes the issues at stake about wage disparities, metropolitan governance structure and policy responses to the fragmentation problem, Section 3 explains the methodology adopted, Section 4 presents the empirical analysis and the results, Section 5 concludes.

2.2 Spatial Disparities and Governance Structure

2.2.1 Wage premia differences across US MSAs: the role of Metropolitan Governance Structure

The issue of spatial disparities in wages and productivity levels is a source of considerable policy concern. In many countries, individual wages exhibit strong and persistent differences not only between rural and urban regions, but also across metropolitan areas. The US territory is no exception: the average high school graduate living in the median metropolitan area earns \$14.1 for each hour worked; the 10th and 90th percentile of the wages distribution for average high school graduates across metropolitan areas are \$12.5 and \$16.5, respectively (Moretti, 2011), which accounts for a 32% difference. On average, a full-time worker between the age of 25 and 60 may experience an increase in the earned nominal wage of about 40% by moving from Abilene, TX to San Jose, CA. The figure applies to high school graduates and it is not the most extreme case: if this worker had a college degree, the increase in nominal wage rise to about 50%. Clearly, land prices vary as well across locations; therefore, variations in real wages are significantly smaller than in nominal terms. Still, differences in nominal wages are not without meaning as they say something about local productivity premia (Combes and Gobillon, 2015; Gibbons et al., 2014). The idea is that a firm set in San Jose, CA would had preferred paying lower wages and land rents by relocating in Abilene, TX if it had had no significant productive advantages in the West Coast. Hence, even though labour markets are not perfectly competitive and labour is barely paid at the value of its marginal product, higher wages can be seen as evidence of higher productivity.

In order to understand the relationship between nominal wages and productivity, let us consider the simplified framework presented in Combes and Gobillon (2015) in which a representative firm is located in MSA a at time t [2]. The firm produces the output $Y_{a,t}$ by means of two factors of production: labour ($L_{a,t}$) and other inputs ($K_{a,t}$) such as land and capital. The profit of the firm is:

[2] For sake of simplicity, the theoretical setting does not consider individual heterogeneity among firms and workers while non-random sorting of skills and industry effects will be considered later in the empirical analysis

$$\pi_{a,t} = p_{a,t}Y_{a,t} - \omega_{a,t}L_{a,t} - r_{a,t}K_{a,t} \tag{2.1}$$

with $p_{a,t}$ the price of the final good, $\omega_{a,t}$ and $r_{a,t}$ the unit cost of labour and other inputs, respectively. A Cobb-Douglas production function such that:

$$Y_{a,t} = \frac{A_{a,t}}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}(s_{a,t}L_{a,t})^{\alpha}K_{a,t}^{1-\alpha} \tag{2.2}$$

where $0 < \alpha < 1$, $A_{a,t}$ is local total factor productivity and $s_{a,t}$ represent local labour skills. In a competitive equilibrium, first order conditions for the optimal use of inputs lead to:

$$\omega_{a,t} = \left(p_{a,t}\frac{A_{a,t}}{(r_{a,t})^{1-\alpha}}\right)^{1/\alpha} s_{a,t} \equiv B_{a,t}s_{a,t} \tag{2.3}$$

Hence, local average nominal wage is related to the level of skills $s_{a,t}$ and a composite local productivity effect $B_{a,t}$.

Differences in local productivity between metropolitan areas, i.e. urban productivity premia which give raise to local wage premia, are strictly related to the size of the cities: it is well known that large cities produce more output per capita than small cities do. The literature has identified one of the causal factors in the economies that accrue from agglomeration, as introduced by Marshall (1890). A high density of firms and workers generates increasing returns to scale at the local level because of the emergence of a number of positive externalities. For example, Duranton and Puga (2004) cited the matching between employers and employee, the learning spillovers and the sharing of infrastructures as well as of facilities. On the latter, Burchfield et al. (2006) found that cities with shared public facilities for the provision of water are more populous than those in which cities aquifers make individual household wells viable. While part of the literature has tried to disentangle the magnitude of the mechanisms at play (Puga, 2010), some scholars proposed other factors explaining urban productivity premia. For instance, a *locus ameneus* may have locational fundamentals that are able to attract people and economic activity *per se*. On the other hand, high-skilled individuals usually prefer to live in denser cities (Bacolod et al., 2009; Glaeser and Resseger, 2010) causing output per worker to increase because of workers sorting. Behrens and

Robert-Nicoud (2015) propose a unique theoretical framework supported by the empirical literature that shows a reduction in agglomeration benefits once productivity endogeneity is taken into account (Melo et al., 2009). Finally, spatial relationships among metropolitan areas matter as well. The literature on agglomeration economies agrees in arguing that wage differences across metropolitan areas may also be determined by proximity to markets for intermediate and final goods (Combes and Gobillon, 2015). In this regard, urban economists usually adopt the concept of market potential: cities should be larger and pay higher wages if they have better access to markets, i.e. if their location has higher market potential (Harris, 1954). The idea has been introduced in the theoretical literature by New Economic Geography scholars (Fujita et al., 2001; Hanson, 2005; Krugman, 1991; Redding and Venables, 2004), according to whom city incomes, distance between cities and the city price indices for manufactured goods are the main ingredients of market potential. Some of these models cast doubt on the unambiguous positive effect of a high market potential; Ioannides and Overman (2004) find that spatial interactions contribute to create city's ability to generate high wages only from the end of the Twentieth century.

In what follows, we use nominal wages as our measure of productivity. Actually, it could be possible to consider wages in real terms, and control for housing/land prices which are likely to influence the costs of factors of production. In the present context, their inclusion should not be interpreted as compensation for low or high wages in equilibrium as in the compensation differentials model of Roback (1982) but just as determinants of productivity. According to Equation (2.3), there exists an inverse relationship between costs of living and nominal wages; in a full spatial equilibrium the correlation is positive. Nonetheless, land prices and wages are simultaneously determined in equilibrium; therefore, the introduction of land/housing prices as control variable in estimating local productivity premia is likely to give raise to serious endogeneity problems. Being aware of the issue, we prefer to concentrate on wages as expressed in nominal terms and to not control for land prices in regressions as land usually accounts only for a small share of input costs. Hence, we take Combes and Gobillon (2015, page 7)'s advice: "As far as the effect of agglomeration economies on productivity only is concerned, nominal wage constitutes the relevant dependent variable and there is no need to control for land prices".

In the present paper, we want to direct the attention towards other factors that we think are able to explain some part of the variability in productivity across metropolitan areas. Our focus is the structure of metropolitan governance, which represents the spatial organisation of formal institutions of local government as well as informal networks in a core-based city region. To clarify the issue, a Metropolitan Statistical Area (MSA) may be conceived as a statistical unit of analysis composed by one or more administratively defined jurisdictions on which population is not uniformly distributed. Usually, metropolitan areas include one central municipality surrounded by a number of outlying jurisdictions that are linked to the former through commuting patterns of people living in the suburbs but working in the city centre as well as by input-output relations among local firms. We define the level of urban *fragmentation* as the number of administratively defined jurisdictions (local governments) that insists on a metropolitan area and the degree of *dominance* of the central jurisdiction as the share of population living in the major municipality. We make an argument to support the thesis that the dispersion of political power, both in terms of numerousness of administratively defined jurisdictions and as distribution of population in a local autonomous economic system, limits the extent to which agglomeration benefits foster local economic productivity. We support the need for a policy response to the issue of poor metropolitan governance but we raise concerns about the effectiveness of existing solutions. Our belief is that only a governance body that resembles a full-fledged regional system can have the capabilities to mitigate the problem.

We collect (and report in Table A3 of the Appendix) a number of descriptive evidences to corroborate our conjectures and to give a flavour of the real dimensions of the question. Let's start by comparing the economic performance in terms of wage premia[3] of two metropolitan areas with a similar level of population such as San Francisco, CA and Atlanta, GA. Wage premium in the former is about 25% higher than in the latter where we observe both a higher number of municipalities (*Fragmentation*) and a more dispersed population (*Dominance*). We notice the same pattern when we look at the figures for New York, NY and Los Angeles, CA with a discrepancy in wage premia favouring the East Cost city. In this case, much

[3] Data refer to the year 2000. Reported wage premia correspond to those estimated in the first-stage of the empirical analysis; therefore, they measure local productivity net of local industrial composition and skill effects.

of the variation in the structure of urban governance comes from differences in the concentration of population as in Los Angeles, CA, it is 2.2 times more dispersed than in New York, NY. On the opposite, the stark difference in the way urban governance is structured between St. Louis, MO and Seattle, WA, is in the number of municipalities that insist on the metropolitan area, being more than four times higher in the former with respect to the other city. At the same time, workers in Seattle benefit from a wage premium that is almost 37% higher than in St. Louis. The descriptive evidences suggest the existence of a relationship between structure of urban governance and wage premia disparities across metropolitan areas, according to which the more concentrated the political power, the higher the returns to labour. By no means the two dimensions that we identify can be considered as substitutes: San Jose, CA and Sacramento, CA, show similar levels of *fragmentation* but in the more productive city (San Jose, CA) population is far more concentrated in the city centre. Moreover, Sacramento, CA does not feature any governance body at the metropolitan level; a reasonable concern may be whether it is the lack to drive its poor economic performance. The hypothesis seems to be invalidated by the presence of a governance body in all the other metropolitan areas that we have just mentioned.

The presence of multiple governments of the same type (either townships, municipalities or counties) within a metropolitan area may create obstacles to the enhancement of metropolitan productivity (Wolman et al., 2011). In the first instance, local governments are governed by officials who are elected by the voters residing within the local jurisdiction. Often, elected local officials tend not to take decisions in a broader, metropolitan perspective, as acting in region's interest is perceived to be counter local interests. Secondly, each local government tries to attract local development within its jurisdictional boundaries in order to receive the revenues from property tax. Hence, the local tax structure within metropolitan areas encourages inter-jurisdictional competition rather than cooperation to enhance productivity within the entire area. Finally, businesses that operate in multiple jurisdictions within a metropolitan area bear higher administrative and regulatory costs imposed by the multiplicity of laws and regulations.

Ahrend et al. (2014b) as well as Kim et al. (2014) argue that municipal fragmentation increases cities' congestion costs because a high number of local governments is more likely to encounter difficulties when it is necessary to coordinate decisions about transport infrastructure investments or effective land use planning. As a consequence, businesses and individuals are less encouraged to locate in a metropolitan area of this type. Furthermore, Storper (2010) argues that formal structure of political institutions determines their efficiency in facilitating economic activity by shaping both the effectiveness of problem-solving as well as the capacity of adjusting to change and capturing new opportunities. In particular, initiatives that require areas are difficult to implement in regions with many small jurisdictions because they can see the light of the day only if a cross-jurisdictional coalition-building is formed.

Finally, Cheshire and Gordon (1998) investigate more deeply which are the factors favouring the formation of cross-jurisdictional clubs. In their original view, agreements between administrative regions belonging to the same local economic system are desirable in order to implement growth promotion policies, such as the construction of relevant infrastructures. The reason relies on the presence of inter jurisdictional spillovers among administrative units of the same metropolitan area: in the case in which the central jurisdiction of a metropolitan area implements a project for the realization of a facility, it will benefit also the other regions belonging to the local economic system. A small number of public agencies belonging to the club and/or the existence of a dominant jurisdiction with the role of leading agency are the two elements that increase the probability that a club will actually be created and maintained at low costs. The argument on governance they make is about its impact on the rate of local economic growth but it can be easily sustained also when talking of local productivity. As a matter of fact, the implementation of growth promotion policies for the creation of quasi-public goods (such as local public infrastructures) is the prerequisite for the activation of the mechanism of sharing facilities that creates localized increasing returns (Puga, 2010).

Opposite to the previous contributions which support centric government structures in metropolitan areas, proponents of public choice theory defend poly-centric or fragmented governance arrangements (Ostrom et al., 1961; Parks and Oakerson, 1989; Tiebout, 1956). In particular, Ostrom (2010) identify three mechanisms that increase productivity in the presence of multiple governmental units. In the first instance, smaller jurisdictions are more effective than larger ones in monitoring the performance of their citizens and the costs of service provisions; secondly, a multiplicity of local governments makes it possible for individuals to choose the jurisdiction in which the mix and costs of public services is closer to their preferences; thirdly, the smaller the administrative units, the better individuals preferences are likely to be represented and citizens may have more say in the decision process.

In general, advocates of fragmented metropolitan governance argue that the higher the number of jurisdictions, the lower the transaction costs for households and firms because of reduced heterogeneity of public policy preferences. The statement draws back to Tiebout (1956) public choice theory, who contends that people, by "voting with their feet", decide to live in the communities that better satisfy their preferences; therefore, the higher the number of jurisdictions among which people can choose, the higher the probability that public services are provided more efficiently because of the high degree of homogeneity of preferences within jurisdictions. On the other hand, centric governance defenders point out how transaction costs are instead reduced when the metropolitan area is little fragmented because it is possible to avoid bureaucratic overlap and law inconsistency; moreover, the region may benefit from economies of scale and scope in providing public goods and services. In this paper, we support the second argument: the absence of inter-jurisdictional spillovers which is taken as given in the public choice literature cannot be assumed in the metropolitan context. Administratively defined regions in a autonomous local economic system are not isolated islands; input-output relationships among local firms as well as commuting patterns create economic linkages across space.

Empirical evidence on the role of governance structure is, in general, rather scant. To our knowledge the only study that analyses the impact of fragmentation on productivity is Ahrend et al. (2014a). Studying Functional Urban Areas in five OECD countries the authors find that cities with more fragmented structures have significantly lower productivity premia. Other studies instead focus on the relationship between governance structure and local growth with conflicting results[4]. Stansel (2005) examines the relationship between local growth and local decentralization in the US metropolitan context and finds that metropolitan economic performance appears to be favoured by the presence of a multiplicity of

[4] The impact of governance structure has been analysed also within the literature dealing with urban sprawl (Carruthers and Ulfarsson, 2002) and fiscal decentralization (Zhang and Zou, 1998).

local governments. Similarly, Hammond and Tosun (2011) find that single-purpose governments per square mile have a positive impact on metropolitan population and employment growth, but they conduct the analysis at the county level and distinguish between metropolitan and non-metropolitan counties. Grassmueck and Shields (2010) argue that results are sensitive to the way fragmentation is measured and, resorting to both an Hirshman-Herfindal-Index and a Metropolitan Power Diffusion Index based on government expenditures, find that fragmentation is associated with increased employment and per capita income growth. In contrast, Paytas (2001) and Hamilton et al. (2004) find evidence in support of the advantages stemming from consolidation by reporting that the level of fragmentation and state centralization are negatively related to metropolitan economic competitiveness. Finally, building on the idea developed by Cheshire and Gordon (1998) that local growth promotion policies are more likely to be implemented the higher the degree of dominance of the central administrative unit within a metropolitan region, Cheshire and Magrini (2009) report a positive impact of dominance on local growth for major European metropolitan areas.

2.2.2 Policy responses to poor metropolitan governance

In the US, there have been some policy responses to tackle the lack of coordination among local governments. In general, metropolitan problems are addressed through two mechanisms: special purpose governments or voluntary agreements. The former, special districts, are meant to provide a specific single public service like, for example, fire, police, water and sewer. Even though the number of local governments, such as municipalities and counties, have remained stable over the decades, the quantity of special purpose governments have increasingly grown. Duckett (2012) and Orfield and Gumus-Dawes (2009) agree in arguing that special districts might not be considered as a solution to the issue of poor metropolitan governance. As a matter of fact, they tend to complicate the problem by adding an other layer to the existing multiplicity of local governments; moreover, they usually lack accountability. Even worse, being special districts the instrument to provide services in unincorporated places outside municipal boundaries, they sustain growth occurring in suburban counties, thus fostering further decentralization and fragmentation (Carruthers and Ulfarsson, 2002).

The second mechanism to deal with coordination issues at metropolitan scale, voluntary agreements, have been implemented in a variety of forms which may be reduced to two broad categories: Council of Governments and Metropolitan Planning Organizations. Council of Governments (COGs) are associations consisting of public officials elected in the major local governments of metropolitan areas. Regional Councils, or COGs, may provide a variety of services ranging from public safety to community development (including both workforce and economic development) and covering also environmental and transportation issues. Their purpose is to establish a consensus about the needs of an area and to provide widely acceptable solutions. Voluntary governance body may assume the form of Metropolitan Planning Organization (MPOs), which are federally mandated and funded transportation policy making organizations made up of representatives from local governments and governmental transportation authorities. Nationwide, substantial differences among MPOs remain, even though recent decades have witnessed a devolution of greater responsibilities for planning and implementations to MPOs. As a matter of fact, states maintain significant discretion over delegating authorities and continue to play a primary role in determining most transportation decisions in metropolitan areas (McDowell and Edner, 2002). These kind of governance body share a twofold problem of under-representation. On the one hand, being conceived in the 1960s, they may not cover completely the current geographic extension of metropolitan areas. On the other, as Sanchez (2006) points outs, central cities are under-represented on governance body voting boards. Governing boards for MPOs and COGs are appointed by local officials, or they may delegated from local jurisdictions. Usually, each participating local government sends a representative to the governance body board regardless of the size of the jurisdiction represented; therefore, the voting mechanism is often non proportional or not weighted by population. As Lewis and Sprague (1997) argue, COGs and MPOs have been structured “towards consensus, with more concern toward representing all local governments on regional boards than on establishing equitable criteria for the representation of the region’s population”.

Some authors indicate multi-purpose regional governance structures with strong powers as the more efficient alternative to deal with the issue of poor metropolitan governance (Orfield and Gumus-Dawes, 2009; Wolman et al., 2011). Few metropolitan areas in the US present these kind of governance bodies that resemble the full-fledged regional system needed to integrate land use, transportation and housing at the metropolitan scale. Orfield and Luce (2009) analyse the cases of the Twin Cities' Metropolitan Council and Portland's Metro which are MPOs regional governing bodies not duplicating functions performed by local governments in the same metropolitan area. In particular, the Minneapolis - St. Paul region have implemented a metropolitan tax-base sharing which requires localities to contribute 40% of their growth in property tax capacity to a regional pool. The collected funds in the pool are then redistributed to local governments within the metropolitan area and municipalities with a lower-than-average tax capacity receive a higher per capita share (Orfield, 2002).

2.3 The Methodology

The methodological framework adopted in the paper follows from recent advancements in the empirics of agglomeration economies (Combes and Gobillon, 2015). Nominal wages are likely to be different across metropolitan areas because of a variety of reasons. In the first instance, industrial composition of the local economy demand higher or lower average wages, depending on which industry, if any, is prevalent in the economic system. Secondly, the average composition of the workforce plays a role as well: for example, we expect highly educated or more talented individuals to receive higher wages. Finally, cities may have specific characteristics that are beneficial to the local economy up to the point of translating into a wage premium. We hypothesise that the structure of urban governance, together with the size of the local economy and the agglomeration spillovers among core-based city regions, play a fundamental role in determining metropolitan areas productivity.

Combes et al. (2008) present a simple model of agglomeration economies on which we rely to provide a clear explanation of our methodological strategy. Let's consider a representative firm in MSA a, industry k at time t which maximizes profits $\pi_{a,k,t}$ with a Cobb-Douglas production function $y_{a,k,t}$ expressed in effective labour and other factors of production. In a competitive equilibrium, first order conditions for the optimal allocation of inputs lead to a (log-linearised) individual wage which is a function of a worker effect ($X_{i,t}$), an industry effect ($i_{k,t}$), a core-based city region effect ($\gamma_{a,t}$), and a shock specific to worker i at time t:

$$log\ w_{i,t} = \beta\ X_{i,t} + i_{k,t} + \gamma_{a,t} + \varepsilon_{i,t} \tag{2.4}$$

The worker effect includes *observable* individual characteristics, such as age and its square value, education, gender, ethnicity and occupation of the respondents. Actually, *unobserved* characteristics, such as skills and abilities, play a role in determining nominal wages as well but measurement difficulties prevent them to be included in a simple repeated cross-section regression, which is in fact our case [5]. Hence, in the absence of a panel structure, the only possibility is to confine time-invariant workers fixed effects in the error term. Nevertheless, we believe that the highly detailed set of *observable* characteristics that we include may reduce the loss of information.

The coefficient $\gamma_{a,t}$ in Equation (2.4) is our parameter of interest as it indicates the wage premium associated to the metropolitan area a at time t net of local industrial mix and local workforce characteristics. Which factors determine such measure of local productivity is the central question of our work; therefore, the identification of the coefficient $\gamma_{a,t}$ deserves special attention. In this context, Combes et al. (2011) discuss the main sources of bias in the identification of agglomeration effects. One of the main empirical issue derives from the fact that the quality of labour is endogenous to the productivity of the metropolitan area: some cities more than others are known to attract younger and highly educated workers or just more talented individuals, who expect to gain more by moving to more productive cities. In particular, the composition of the workforce is strictly connected to the size of the city. The complementarity between cities and skills has been documented by a number of studies (see, for example, Glaeser and Resseger, 2010) and may occur for two reasons. On the one hand, the initial distribution of workers' skills may vary according to the size of the city with larger urban agglomeration having, on average, higher skill level. In fact, better schools and universities in denser cities may increase the productivity of natives; moreover, learning at the workplace may be faster in denser cities (De la Roca and Puga, 2012; Glaeser and Mare, 2001). On the other hand, workers may sort by skills and more talented individuals tend to co-locate in larger cities (Bacolod et al., 2009): for

[5] The IPUMS sample that we use does not allow us to adopt a panel specification because individual identifiers have not been provided due to confidentiality restrictions.

instance, workers with a better learning potential may choose to go to denser cities where more learning takes place. In econometric terms, the problem translates into a positive covariance between the coefficient representing the local wage premium and the *observable* and *unobservable* characteristics of the workforce.

Ideally, the problem of endogenous labour quality could be solved by adopting a two-stages procedure and relying on a panel data structure in the first stage where it would be possible to control for both *observable* (skills distribution among metropolitan areas) and *unobservable* workers' characteristics (non random sorting of skills) (see, for example, Combes et al., 2008; Mion and Naticchioni, 2009). In particular, it would be possible to estimate wage premia by means of a metropolitan dummy variable having some workers that remain in each of the metropolitan areas between any two consecutive periods of time and a flow of workers from each of the metropolitan areas. Differences between areas over time are identified by workers that move across areas; workers that remain in the same metropolitan area provide the identification for changes over time for their area. Hence, in a panel specification, area fixed effect may be estimated separately from individual effect through movers' choice of location.

Here, we adopt a different identification strategy in order to overcome the limitations due to the structure of our dataset, which is a simple cross-section repeated over three decades. The general framework follows Combes et al. (2008) and we maintain the two-stages procedure where the first stage is implemented on individual data while metropolitan statistical areas become the unit of observation of the second stage. The aim of the first stage is that of estimating a measure of metropolitan wage premium, that is the part of nominal wages that remains to be explained after having considered the effect of the local industrial composition, the average workers characteristics and the non-random skill sorting across cities. The likely sources of variation of wage premia are then tested in the second stage of the empirical model and include the size of the local autonomous economic system, the spatial spillovers among cities, the structure of the metropolitan governance as well as the effectiveness of the policy solutions implemented in response to the problem of poor governance.

Our main concern in the first stage is to distinguish the contribution of the "place" from that of the "people" in the formation of individual wages. We believe that the identification can be achieved by introducing an instrument for the metropolitan area dummy variable. In particular, the *current* metropolitan area of residence is instrumented with the corresponding five-years lagged. In this way, the metropolitan area of *previous* residence is used as an instrument for the *current* one. For the whole dataset, about 77% of respondents have not moved from one metropolitan area to another in the 5 years interval. The high correlation assures us that the relevance condition for the validity of the instrument is satisfied, and we can move to the discussion about the exogeneity condition. In particular, we want the instrument to be uncorrelated with the error term; in our specific case, with the *unobserved* workers characteristics contained in the error term. Our identification strategy relies on the non-random sorting of skills: if the individuals that moved in the previous period are the more talented looking for better opportunities in more productive cities, then using the *previous* metropolitan area of residence rather than the *current* one avoids the over-estimation of the "place" contribution. Let's consider, for example, an individual that earns a nominal wage higher than a colleague working in the same industry but in a different place. The wage premium may be due to the fact that in his metropolitan area agglomeration benefits foster local productivity and nominal wages or that the individual is simply more talented than the colleague. If we try to identify the contribution of the location characteristics by imputing the *current* MSA of residence, we over-estimate it. Instead, if we use the *previous* residence (and it is different from the current one), he will be excluded from the estimation of the "place" effect of the *current* MSA of residence. The area fixed effect is correctly identified if he is a high-skilled individual who has moved to a city that is more productive than the previous one. This is the pattern described by Glaeser and Resseger (2010) and Bacolod et al. (2009). On the contrary, if skills sorting is random, the problem of endogenous quality of labour ceases to exists and the use of the instrument cannot be harmful for the estimation purposes because it captures a random process.

To sum up, the first-stage equation that we estimate is:

$$log\ w_{i,at} = \beta X_{i,at} + \gamma_{at} d_{i,at-5} + \mu_t i_{i,t} + \varepsilon_{i,at} \tag{2.5}$$

where $w_{i,at}$ is the nominal wage of individual i at time t who works in Metropolitan Area a at time t, X is a vector of individual characteristics, $d_{i,at-5}$ is a vector of dummy variables that take value 1 if the individual used to live in Metropolitan Area a five years before and $i_{i,t}$ is the vector of industry dummies. The estimated coefficients γ_{at} represent that part of wages variability that is not explained by workforce or industrial composition [6]. Details on the Census data used and on the construction of the set of variables are available in the Appendix.

Subsequently, the second stage of the estimation procedure entails the use of location fixed-effect as dependent variable, which is regressed on the set of explanatory variables of interest:

$$\hat{\gamma}_{a,t} = \theta T_t + \delta Z_{a,t} + u_{a,t} \tag{2.6}$$

where $\hat{\gamma}_{a,t}$ are the estimated coefficients of the metropolitan areas a dummy variables obtained from the first stage regression, T_t are additional year fixed effects, $Z_{a,t}$ is a matrix containing the explanatory variables and $u_{a,t}$ is the error term. The objective of the second stage is the assessment of the relative importance of the size of the local economy, the structure of urban governance and the spatial extent of agglomeration effects in explaining the area-year fixed effects estimated in the first stage.

The *size of the economy* may be measured in terms of employment, population or production. Ciccone and Hall (1996) suggested to use the number of individuals per unit of land and Briant et al. (2010) argued that the adoption of density measures, instead of population level, should reduce the Modifiable Areal Unit Problem even though shape distortions remain a second order concern with respect to correct model specification. In general, both density and the size of the location should have a positive impact on local productivity if agglomeration gains outweigh agglomeration costs; therefore, it would be worthwhile to consider both effects in a logarithmic specification (Combes and Gobillon, 2015). In particular, by introducing *density* and *land area* among the explicative variables of Equation (2.6), it is possible to derive conclusions about the gains from increasing the number of people while maintaining land fixed (or viceversa) and the effect of land area for a given population level which is equal to the difference between the effect of land area (with constant population) and the effect of density (with constant land). It should be noted that the conclusion about the presence of agglomeration

[6] In order to catch the location specific effect, we hypothesize that the respondents used to live and work in the same place. While the assumption would be barely defensible in many other contexts, it turns out to be quite reasonable when the unit of analysis is the metropolitan area that represents a local economic system as self contained as possible in terms of commuting patterns.

benefits are not invalidated even though the last effect turns out to be negative. As a matter of fact, when using density and land area, agglomeration gains exist when any of the estimated coefficients is significantly positive.

The second set of explanatory variables aim at assessing whether productivity benefits associated to agglomeration economies may be enhanced by the presence of a small number of local governments within the same metropolitan statistical area or by the presence of a dominant municipality. In particular, the two dimensions of the structure of urban governance that will be taken into account are the *level of fragmentation* and the *degree of dominance*. The former is computed as the number of municipalities in metropolitan areas in 1980, 1990 and 2000 as defined by the Office of Management and Budget. The latter is the ratio of the population living in the largest city of each metropolitan area to that of the metropolitan area in contemporaneous configurations for the three decades. Note that the *degree of dominance* needs to control for territorial extension of the central city in order to take into account, for example, the case in which the central city is consolidated with the county[7]. On the other hand, the *level of fragmentation* does not need to control for the Metropolitan Area size[8], since this dimension has already been taken into account by including *density* and *land area*. A final set of explanatory variables include the policy responses to the issue of fragmented metropolitan governance. In particular, we consider: presence of Council of Governments (*COGs*) and Metropolitan Planning Organizations (*MPOs*), variety of services provided by the governance bodies (Transport, Environment, Community Development, Public Safety, Economic Development and Workforce Development), *Geographic Adherence* of Regional Councils to metropolitan areas, number of *special purpose governments* and existence of a metropolitan *general purpose government*. Table A2 in the Appendix presents the complete list of explanatory variables with a synthetic description and the sources of the data. An exhaustive explanation of the way in which the measure of *Geographic Adherence* has been computed is in the Appendix as well.

[7] The consolidated city-county included in the analysis are Augusta-Richmond County, GA; Indianapolis-Marion County, IN; Jacksonville-Duval County, FL; Louisville-Jefferson County, KY; Nashville-Davidson County, TN; Macon-Bibb County, GA.

[8] Usually the literature adopts the number of municipalities per 100,000 inhabitants (Stansel, 2005).

2.3.1 Substantive spatial dependence

A simple way to assess the spatial extent of agglomeration effect is that of relying on the concept of market potential, which is a proxy of the goodness in the access to the market. Once the specified equation to be estimated contains on the RHS both density and market potential as measured in terms of density, it resembles the generic formulation of a ''Spatial Lag of X" (SLX) model (LeSage and Page, 2009), in which the independent variable is included with a spatial lag. As argued by Gibbons and Overman (2012), the use of a SLX specification helps to overcome the identification problems that are typical in spatial econometrics, i.e. a) the impossibility to distinguish different econometric specifications without assuming hypothetical prior knowledge of the data generating process and b) the ''reflection problem" according to which it is not possible to recover the unknown parameters of a model from their reduced form specification if it includes both exogenous and endogenous characteristics of the neighbours.

There exists a number of variants for computing market potential; in fact, it is possible to consider either population, employment or production in levels or density forms. As shown by Combes and Lafourcade (2005), all the different formulations measuring market potential are highly correlated but if density is used to measure the size of the local economy, computing market potential using densities is more consistent. In what follows, the market access variable used is the (log) of market potential computed from the density of neighbouring areas:

$$MP_{a,t} = \sum_{a \neq l = 1}^{n} w_{a,l} \, den_{l,t} \tag{2.7}$$

where $w_{a,l}$ are the elements of a spatial weighting matrix, W, providing a description of the interactions between spatial units.

In order to deal with the uncertain functional form of spatial agglomeration effects, we introduce a parameterized distance based weights matrix where the distance decay parameter is estimated by using a nonlinear estimation technique, as suggested by Vega and Elhorst (2015) and recently applied to the local multipliers analysis by Gerolimetto and Magrini (2015). By adopting this approach, it is possible to capture more information on the way in which inter-dependencies between spatial units are structured. Hence, the analysis consider the possibility that the rate of decline of agglomeration benefits is sharper than the one determined simply by the inverse of the distance. In particular, we employ a simple inverse distance matrix with a threshold:

$$w_{a,l} = \begin{cases} 1/d_{al}^{\alpha}, & \text{if } 0 \leq d_{al} \leq d \\ 0, & \text{if } d_{al} > d \end{cases} \tag{2.8}$$

where α is the distance decay parameter, d is a distance threshold and d_{al} represents the distances between location a and l. Vega and Elhorst (2015) provide the details about the nonlinear estimation technique of the distance decay parameter. Row-normalization of W based on inverse distance make the economic interpretation of the weights to be no longer valid in terms of distance decay. Hence, we apply a min-max normalized matrix Kelejian and Prucha (2010) obtained by dividing each element w_{al} by

$$\tau = min \left\{ max_a \sum_{l=1}^{n} w_{al},\ max_l \sum_{a=1}^{n} w_{al} \right\} \tag{2.9}$$

2.3.2 Endogenous quantity of labour

A further empirical concern that arises involves the possibility that some local characteristics are endogenous to local wages: a metropolitan area that experiences a positive shock may increase its size because of migrations. In this case, there may be a reverse causality problem that is going to bias the estimates. In order to deal with the endogeneity issue, we adopt an instrumental variable approach and we assume that endogeneity may be caused by *contemporaneous local shocks*, as in Ciccone and Hall (1996). So far, the literature have adopted a number of instruments for solving the problem of endogenous quantity of labour. For example, Ciccone and Hall (1996) use long lags of population, Combes et al. (2010) opt for the geological characteristics of regions and Combes et al. (2008) choose some measures of geographical periphery.

The strategy that we adopt here involves the use of a Bartik instrument (Bartik, 1991) for density. For each metropolitan area, we calculate the number of workers in each sector with respect to total employment in 1970[9]. Each metropolitan area

[9] The industries that have been considered using the SIC classification are: Construction, Manufacturing, Transport and Public Utilities, Wholesale Trade, Retail Trade, Finance Insurance

has an *imputed rate of growth* which is the sectoral nationwide rate of growth that would have been if its contribution was set to zero. The sum of the *imputed rate of growth* weighted by the initial shares of employment constitutes the metropolitan *counter-factual rate of growth*. The *counter-factual level* of employment is then determined by applying the *counter-factual rate of growth* to the actual level of local employment at the beginning of the period and it is used as instrument for density. The use of the Bartik instrument helps to get rid of city-specific shocks and to isolate exogenous shifts in the demand for labour. The counter-factual rate of growth of employment in Metropolitan Area a ($\Delta B_{a,t-k\ to\ t}$) is computed as:

$$\Delta B_{a,t-k\ to\ t} = \left[\sum_{I \in Ind} \frac{empl^I_{a,t-k}}{\sum_{I \in Ind} empl^I_{a,t-k}} * \Delta\ ln\ \left(\sum_{l \in Reg \neq a} empl^I_{l,t-k\ to\ t} \right) \right] \tag{2.10}$$

where $empl^I_{a,t-k}$ is employment in industry I, region a, time t and $\delta_{t-k\ to\ t}$ indicates the differences between years $t-k\ to\ t$. The first term on the RHS represents the share of employment in region a that is employed in industry I, while the second term is the change in employment, in industry I, for all other regions. From the above computation derives the *counter-factual level* of employment which we use as instrument for the level of population density.

2.3.3 The *floating area approach*

The geographic definition of the area that corresponds to a local and autonomous economic system is not constant over time, as the pattern of centralization and decentralization evolves, so the metropolitan area changes its boundaries and internal composition. Hence, metropolitan areas are different both in static as well as dynamic terms. The former source of variation deals both with the number of administratively defined jurisdictions that shape the statistical unit of analysis as well as with the concentration of population in the central municipality; the latter derives from the evolution of the original configuration over time. Usually, the literature considers the metropolitan areas' delineation that is in effect at a precise moment in time, but does not consider the evolution of MAs boundaries even though the time frame of the analysis covers various modifications in the

and Real Estate, Services; the source of the data for local industrial employment is the Bureau of Economic Analysis, which provides information at the metropolitan level.

delineations. Hence, in the case of a city that has expanded over time, either the definition is the initial one and the level of fragmentation is underestimated, or the definition is the latter one, and it is overestimated. Let's think, for example, to the spatial variation of Atlanta, GA. In 1960, the city consisted of five counties, by 1990 it had expanded to encompass twenty counties. Figure A1 in the Appendix shows the spatial evolution of the metropolitan area of Atlanta, GA, as defined by the Office of Management and Budget for the years 1970, 1980, 1990, 2000. If we adopt the initial definition, Atlanta will show a low number of local governments for the whole time series; on the other way round, by accepting the final delineation and fitting it backwards, Atlanta will be characterized by a high level of horizontal dispersion of power among individual lower-level governments.

Few authors have tackled the change in the boundaries issue (see, for example, Gottlieb, 2006; Nucci and Long, 1995). Recently, Ferranna et al. (2016) analyse how the spatial evolution of core-based city regions affects the dynamics of the cross-sectional distribution of US MSAs per capita average incomes. The authors compare the convergence results deriving from the application of different approaches to define MSAs over time: the *fixed area* and the *floating area*. The former uses the same designation of counties over a series of decades, which may be beginning, ending or some intervening date; the latter uses the universe of metropolitan counties at the beginning of each decade. Table A1 in the Appendix reports the mean values for density, land, fragmentation and dominance based on the *floating area* and on the *fixed area* approaches. Fragmentation is here defined as the number of administrative units (counties) that compose the metropolitan area per 100,000 inhabitants; dominance is the percentage of population living in the central city. By reading across rows, one can compare the average values over the three decades (1970, 1980, 1990) using the same universe of counties (i.e. *fixed area approach*). By reading down the principal diagonal of each panel, one can compare average values using the *floating area approach*. Percentage change with respect to the latter method are reported in the last three columns. Data in Table A1 indicate that average values for land and fragmentation (density and dominance) are, in general, lower (higher) if we use the fixed area approach based on earlier years. In order to obtain more reliable estimates, we suggest to evaluate the impact of the local government structure by adopting the *floating area approach*. In particular, following Ferranna et al. (2016), the evaluation is conducted in accordance with the time-frames defined by the Office of Management and Budget's (OMB) official updates of the boundaries delineations [10].

2.4 Empirical Analysis

The importance of metropolitan governance structure in determining wage premia has been tested for a sample of 182 metropolitan areas in the US, over a time period ranging from 1980 to 2000. A map of the metropolitan areas included in the analysis is reported in Figure A2 in the Appendix. The main source of the data for the first-stage of the regression is the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al., 2015) and the samples used are 1% samples for the years 1980, 1990 and 2000. The second stage of the regression uses data from the Bureau of Economic Analysis at the county level, then aggregated at the metropolitan level according to the official delineations provided by the Office of Management and Budget for the three decades. Table A2 in the Appendix provides a list of all the variables included in the Second Stage of the estimation procedure, as well as a brief description and the specific sources of the data. Corresponding descriptive statistics are reported in the subsequent Table A4. Finally, a list of metropolitan governance bodies is available in Table A5.

2.4.1 First Stage Estimation Results

The following Table 2.1 presents the results in a compact form for the set of workers observable characteristics, industry dummies as well as Metropolitan Area fixed effects interacted with time dummies[11]. In the Appendix we report three maps (Figure A3, Figure A4, Figure A5) of the metropolitan areas included in the analysis showing estimated local productivity by decade.

In order to evaluate the relative importance of area fixed-effect with respect to either worker characteristics, industry or time fixed effect, Table 2.2 summarizes

[10] The adopted methodology is consistent with the Integrated Public Use Microdata Series's definition of the geographical unit of analysis (Ruggles et al., 2015). In IPUMS samples, the variable that identify the Metropolitan Area in which the respondent works generally correspond to contemporary OMB delineations.

[11] Table A6 in the Appendix reports the results in more details

Table 2.1: First Stage Specifications Results

	(I)	(II)	(III)	(IV)
Age	0.0614***	0.0564***	0.0561***	0.0536***
	(85.47)	(84.27)	(84.08)	(81.57)
Age^2	-0.0006***	-0.0006***	-0.0006***	-0.0005***
	(-74.63)	(-69.71)	(-69.48)	(-67.22)
Ethnicity	0.232***	0.159***	0.158***	0.156***
	(119.78)	(88.46)	(87.47)	(87.66)
Gender	0.242***	0.246***	0.239***	0.221***
	(160.16)	(176.81)	(170.43)	(148.82)
Very High Education		0.672***	0.674***	0.664***
		(242.70)	(238.20)	(231.14)
High Education		0.382***	0.386***	0.373***
		(140.65)	(141.05)	(136.97)
Medium Education		0.227***	0.232***	0.220***
		(85.10)	(86.76)	(83.22)
N	540740	540740	540740	540740
R^2	0.9626	0.9682	0.9684	0.9693
MSA X Year Dummies	Yes	Yes	Yes	Yes
Occupation Dummies	No	No	Yes	Yes
Industry Dummies	No	No	No	Yes

MSA clustered t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reference categories for OCCUPATION: Occupation=Service Occupations; for EDUCATION: Education=Low; for GENDER: Gender=Female; for ETHNICITY: Ethnicity=Not White; for INDUSTRY: Industry=Personal Services.

the explanatory power of the variables on the RHS of Equation 2.5 as in Abowd et al. (1999). In particular, the table reports the standard deviation of the effect of the (group of) explanatory variables and their correlation with (natural logarithm of) wages, industry fixed effects and de-trended area fixed effects. The *effect of each variable* has been constructed by multiplying its coefficient by its value for each observation; for a group of variables the sum of the effects is computed. The total number of observations is 540,740 and all correlation between coefficients that are not orthogonal by definition are significant at 1% level. Subsequently, we derive the variability of the effect of each variable across workers. The table should be interpreted as follows: when the effect of a variable has a large standard deviation and it is highly correlated with wages, then the variable of interest has a large explanatory power. On the opposite, the variations of wages could be explained only marginally if the effect of a variable has a small standard deviation and a small correlation with wages.

Table 2.2: Variance Decomposition

Effect of	Std.Dev.	Simple correlation with:		
		$\ln w$	μ	$\gamma - \theta$
log of wages ($\ln w$)	0.590	1.000	0.181	0.139
worker's characteristics (βX)	0.296	0.511	0.049	0.012
industry fixed effects (μ)	0.098	0.181	1.000	0.023
area fixed effects ($\gamma - \theta$)	0.153	0.139	0.023	1.000

Notes: Area fixed effects are de-trended using the time fixed effects θ estimated in the second stage.

Table 2.2 indicates the *effect of*:

- *workers' observable characteristics*, which has the largest explanatory power. The standard deviation (0.296) is quite large with respect to (log of) wages' variability (0.590). Moreover, the correlation between workers' characteristics and wages is large (0.511). All of the others variables, or group of, show lower standard deviations and correlation with wages than the set of workers' characteristics. This set includes: age and its square, gender, ethnicity, education and occupation.

- *industry fixed effects*, which has a quite small explanatory power. In particular, even though the correlation with wages (0.181) is quite high, the standard deviation (0.098) is less than one sixth of that of worker characteristics.

- *area fixed effects*, which has a substantial power in explaining wages' variability, still lower than that of worker fixed effects. In fact, the correlation with (ln of) wages is 0.139 while the standard deviation is 0.153, one fourth that of wages. In order to distinguish its explanatory power from that of time fixed effect, area fixed effects have been de-trended using the time fixed effects (θ) estimated in the second stage.

In sum, the results of the First Stage estimation are in line with previous studies. For example, Combes et al. (2008) estimate a model of wage determination across local labour markets using a very large panel of French workers and find that the set of variables with the strongest power in explaining wages' variability is worker fixed effects, followed by area-year fixed effects. Differently from the present analysis, they include also within-industry interactions (number of establishments and industry share in employment) among the explanatory variables, but these turn out to be of modest interest in explaining wages' differences across locations.

2.4.2 Second Stage Estimation Results

The coefficients for the area fixed effects estimated in the First Stage are then used as dependent variable in the Second Stage of the regression (Equation 2.6) which is estimated by using a SLX-IV method. Table 2.3 reports the main results. The model has been estimated by using several specifications in order to: firstly, assess the negative impact of poor metropolitan governance, i.e. highly fragmented metropolitan areas without a dominant jurisdiction; secondly, evaluate the various policy responses to the coordination difficulties and, finally, to test the hypothesis about the benefit deriving from having a general-purpose regional structure with extensive powers.

In all the specifications, the explanatory variables introduced are density, land area, market potential and the dimensions of urban governance structure, i.e. the *degree of dominance* and the *level of fragmentation*. The coefficient of density is around 8% , is quite large with respect to the literature: Melo et al. (2009) show that there is a great deal of variability in the magnitude of the estimates, although they are usually found to be positive. The coefficient on land area is smaller than that on density: an increase in population through higher density has a much larger effect on wages than the one that we would have obtained if the same increase in population had left density constant by increasing land area. The estimated coefficients of the variables that proxy the structure of urban governance are both significant and indicate how agglomeration benefits are penalized in the case of less consolidated metropolitan areas. As a matter of fact, a metropolitan area with ten percentage more administrative units than another of the same size, experiences wages that are between 2.0% and 3.0% lower. Moreover, a ten percentage point decrease in the share of population living in the central city is estimated to reduce productivity by a small on average but highly significant amount, that is between 0.7% and 0.8%. The *distance decay parameter* is non-linearly estimated according to the procedure developed by Vega and Elhorst (2015). Its estimation provides information on the way spatial interactions fade as the distance between units increases which would not been otherwise obtained by imposing it beforehand.

The estimated distance decay parameter ranges between 1.7 and 2.0, meaning that the rate of decline of agglomeration benefits is sharper than the one determined by the inverse of the distance. The coefficient for *market potential* is positive and highly significant as it ranges between 2.0% and 2.2%. The finding is in line with the literature; for example, Briant et al. (2010) and Combes et al. (2008) have similar figures in their studies.

All the specifications introduce the instrument for density, in order to control for the likely endogeneity deriving from reverse causality with wages. The instrument is the *counter-factual level of employment* that would have been achieved if the local economy was growing according to the *counter-factual growth rate* computed as the weighted average of the *imputed growth rate* (nationwide sectoral growth rate net of the individual contribution), where the weights are the initial shares of local industry employment. The instrument has a strong power in predicting density and the R-squared of the first stage estimation of the two-stages least squares is 0.91 and performs successfully in both the under-identification and weak identification tests. As a matter of fact, the relevance of the instrument cannot be rejected at the 1%, 5%, or 10% confidence level; therefore, the model is identified. Moreover, the instrument results to be not weak, with a Wald F-statistics over 300, far higher than the 10% critical value computed by Stock and Yogo (2005). The diagnostics reported in Table 2.3 clearly confirm that the level of metropolitan density is indeed endogenous at a confidence level of 1%. A second instrument is introduced, which is the spatial lag of the *counter-factual rate of growth*. The p-value for the over-identification test arrives at 0.66 indicating that both the instruments are valid (uncorrelated with the error term).

In Table A7 in the Appendix we report the sensitivity of the results to variations in the shape and size of the spatial units of analysis. The data used in the model which estimation results are reported in the first (second) column consider the metropolitan areas as they are defined in the initial (final) period, i.e. 1980 (2000). In both cases the specification used is the IV-SLX. Comparing the figures with the findings reported in Table 2.3, it turns out that estimates for metropolitan governance structure are upward biased when adopting a constant definition of the metropolitan area. Still, the findings are in line with the ones derived by applying the floating definition approach; therefore, results are robust to the modifiable areal unit problem.

Stated the negative impact of poor metropolitan governance, let's turn to the policy responses that have been applied to some metropolitan areas. Firstly (**I**) a measure of state centralization is introduced, in order to capture a possible state component in the variability of urban governance structure (McDowell and Edner, 2002). We consider the State Centralization Index (SCI), following Paytas (2001) and Grassmueck and Shields (2010). The SCI has been formulated by Stephens (1974) and updated by Stephens and Wikstrom (1999). The index rises with the level of state centralization, classified as the extent of services delivered, financial responsibility for public services and personnel adjusted for state and local differences in labour inputs versus inputs of cash and capital. The index turns out not to be significant in explaining wage differentials among metropolitan areas. A state component is already contained in the (**II**) specification, where we add two dummy variables indicating, respectively, weather a Council of Government or a Metropolitan Planning Organization act over a significant part of the metropolitan area. Both variables are highly correlated with a state dummy and present a statistically negative coefficient, pointing out how the costs related to the implementation of a governance body based on voluntary agreements between local jurisdictions outweigh benefit. The finding is in line with the literature pointing out the unbalanced representativeness of COGs and MPOs due to a voting system non proportional or not weighted by population (Lewis and Sprague, 1997; Sanchez, 2006) and the bureaucracy they add to that already existing. A detailed analysis of the services provided by Council of Governments may be found in specification (**III**). In most of the cases, whatever the services provided by the COGs, the results are not significant in statistical terms. It may be that COGs are duplicating functions provided by local governments in the metropolitan area or that they do not respond efficaciously to local preferences. The only service that has a negative but significant impact on metropolitan productivity is public safety, that maybe introduce a cost to regional economies by crowding out resources to favour security needs of citizens living in the middle-class outlying jurisdictions, which have more voice than central cities in voting boards.

Specification (**IV**) tackles the issue of geographic representativeness of Regional Councils. A dummy variable have been introduced in order to capture the geographic adherence of COGs to correspondent metropolitan area. In order to construct the variable, we compute three measures by intersecting population in metropolitan area and population in the governance body and dividing it by either population in MA (1) or population in the COG (2), and by calculating the ratio between population in the governance body with respect to that in the metropolitan area (3). By combining these indexes, six scenarios may be detected: 1) the COG is entirely contained in the territory of the metropolitan area; 2) the COG extends beyond the boundaries of the metropolitan area; 3) the COG is larger than the metropolitan area but doesn't contain it entirely; 4) the COG is smaller than the metropolitan area but it extends outside its boundaries; 5) the COG and the MA perfectly coincide; 6) there's no COG in the MA. The variable introduced in the analysis (Geographic Adherence) tests the hypothesis that perfect coincidence or slight mismatch between the two entities with one containing entirely the other , are the preferred solutions. The coefficient estimated for the dummy variable is in fact positive and statistically significant, which supports the correctness of our statement. The contribute of COGs and MPOs in alleviating coordination difficulties when metropolitan areas are highly fragmented is evaluated in (**V**) where the impact of interaction variables between both COGs and MPOs with fragmentation are assessed. The former is only marginally significant while the latter is not significant at all, meaning that the penalty due to a marginal increase in the number of local governments is not going to be reduced in the case in which a governance body is present in the metropolitan area.

Alternatively or side by side to COGs and MPOs, special districts may be created to address local needs of population living in outlying counties. We added the number of special purpose governments to the (**VI**) specification observing that they do not significantly affect average wages in metropolitan region. As stated by Duckett (2012) and Orfield and Gumus-Dawes (2009) special districts tend to complicate the problem by adding to local governments. Finally, we test hypothesis about the effectiveness of general purpose regional governments with extensive powers, as those in Twin Cities, MN and Portland, OR. Hence, a dummy variable that takes values one in these two cases is introduced in specification (**VII**), where it turns out to be positively and marginally significant. Actually, Minneapolis - St. Paul, MN is the only metropolitan area to have implemented a metropolitan tax-base sharing according to which revenues from property taxes are redistributed favouring low than average per capita income municipalities (Orfield, 2002). This strategy seems to be the only one (**VIII**) to give positive results. As a matter of fact, consolidated government like that of Twin Cities is expected to increase local productivity by about 6%.

Table 2.3: IV-SLX Estimation Results

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Density	0.0836***	0.0834***	0.0816***	0.0835***	0.0827***	0.0811***	0.0823***	0.0823***
	(12.40)	(12.62)	(12.96)	(12.91)	(12.93)	(13.03)	(13.01)	(12.62)
Land	0.0834***	0.0760***	0.0766***	0.0766***	0.0748***	0.0714***	0.0753***	0.0750***
	(12.15)	(10.99)	(11.49)	(10.94)	(10.63)	(9.83)	(11.43)	(10.82)
City Land	-0.0272***	-0.0241***	-0.0222***	-0.0256***	-0.0252***	-0.0242***	-0.0257***	-0.0250***
	(-4.83)	(-4.34)	(-4.28)	(-4.66)	(-4.89)	(-4.68)	(-4.81)	(-4.80)
Market Potential	0.0222***	0.0201***	0.0201***	0.0211***	0.0207***	0.0210***	0.0216***	0.0219***
	(6.60)	(6.11)	(6.06)	(6.14)	(5.94)	(6.11)	(5.97)	(6.24)
Fragmentation	-0.0214***	-0.0199***	-0.0237***	-0.0203***	-0.0340***	-0.0294***	-0.0297***	-0.0301***
	(-4.36)	(-4.30)	(-5.46)	(-4.37)	(-4.65)	(-5.19)	(-5.11)	(-4.97)
Dominance	0.0882***	0.0734***	0.0811***	0.0712***	0.0709***	0.0665***	0.0731***	0.0721***
	(3.54)	(3.16)	(3.56)	(3.12)	(3.12)	(2.98)	(3.33)	(3.28)
Distance Decay	2.051***	1.926***	1.836***	1.776***	1.745***	1.747***	1.725***	1.734***
	(9.11)	(6.11)	(6.02)	(5.64)	(5.79)	(5.39)	(5.66)	(5.79)
SCI	0.00802							
	(0.25)							
MPOs		-0.0186***	-0.0137**	-0.0162***	-0.0415**	-0.0136**	-0.0153**	-0.0151**
		(-3.26)	(-2.43)	(-2.90)	(-2.01)	(-2.33)	(-2.62)	(-2.72)
COGs		-0.0269***		-0.0311***	-0.0805***	-0.0684***	-0.0775***	-0.0789***
		(-4.86)		(-5.39)	(-3.71)	(-3.27)	(-3.66)	(-3.69)
Transport			-0.0121*					
			(-1.65)					
Environment			0.0141**					
			(1.95)					
Community			0.006					
			(0.79)					
Public Safety			-0.0321***					
			(-4.08)					
Economic Development			-0.0251*					
			(-2.04)					
WF Development			0.00476					
			(0.40)					
Geographic Adherence				0.0237**	0.0228**	0.0244**	0.0238**	0.0237**
				(2.55)	(2.39)	(2.53)	(2.57)	(2.52)
COGsXFragmentation					0.0164**	0.0123**	0.0153**	0.0157**
					(2.48)	(2.02)	(2.62)	(2.43)
MPOsXFragmentation					0.0096			
					(1.48)			
Special Districts						0.0052		
						(1.68)		
General Purpose							0.0353*	
							(1.86)	
Twin Cities								0.0606***
								(3.42)
N	546	546	546	546	546	546	546	546
MSA	182	182	182	182	182	182	182	182
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Over Identification	3.76	0.95	0.20	0.47	0.71	0.29	0.52	0.53
(p)Over Identification	0.05	0.32	0.66	0.52	0.40	0.59	0.47	0.47
Weak Identification	330.25	361.32	320.86	353.58	353.81	291.92	345.85	345.71
Under identification	105.89	104.91	115.73	104.26	109.05	112.47	102.96	102.54
(p)Under identification	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Endogeneity	12.18	9.37	8.28	10.43	10.92	12.12	11.06	8.62
(p)Endogeneity	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: t statistics in parentheses. Bootstrap Robust Standard Errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.5 Conclusions

The impact on local productivity of the way in which urban agglomerations are governed has received little attention, with few exceptions (Ahrend et al., 2014a). However, this paucity of empirical studies is in stark contrast with anecdotal evidence suggesting formal structure of metropolitan governance as a channel of direct intervention for spurring local productivity. For example, local governments fragmentation has been indicated as the major cause of St. Louis inability to solve collective challenges resulting in social tensions in places like Ferguson. Back in 1876, the city of St. Louis separated from St. Louis County in order not to provide any more services to the outlying areas. Moreover, St. Louis County contains 90 municipalities, which rely mainly on revenue generated from traffic tickets and related fines. Since 1960s, population loss due to migrations from the Rust Belt to the Sun Belt has been later followed by a white flight from the city to the outlying places, leaving St. Louis suburbs with a black-majority and a white-power structure (Badger, 2015; Smith, 2014). And again, local economies and commuting patterns do not stop at municipal borders. Nonetheless, there are numerous cities where certain transport modes end at administrative boundaries. This is the case of Atlanta metropolitan area (150 cities spread across 29 counties), whose mass transit system does not extend far enough into the suburbs where workers live, causing them to waste a lot of time in commuting. The Texas Transportation Institute has estimated traffic congestion to cost extra 51 hours of commuting time each year to each Atlanta commuter and an overall sum of more than $3.1 billion a year in lost time, fuel and environmental degradation (Chapman and Trubey, 2015). More generally, the narratives show how the presence of many small jurisdictions may hinder the effectiveness of problem solving and adjustments to change at the metropolitan scale (Storper, 2010).

The paper tries to shed some light on the role played by metropolitan governance structure by investigating the determinants of spatial wage disparities among metropolitan areas in the US. Productivity differentials are estimated by means of a two-steps procedure, which allows us to distinguish between people and place contribution in explaining them. The part of wages variability that is not explained by observable workers characteristics or industry fixed effects represents productivity premia, which are then studied in relation to four broad drivers. The first regards the size of the local economy, and deals with population density and metropolitan land area; the second relates to the spatial extent of agglomeration benefits and it is summarized in the market potential notion, the third concerns the structure of urban governance and the fourth investigates the policy responses to the problem of fragmentation.

The results indicate that agglomeration externalities are penalized when the metropolitan area is highly fragmented into many administratively defined jurisdiction or when the population is not concentrated in the central city. Moreover, the presence of voluntary governance bodies has a negative impact on wage premia, indicating that costs related to the implementation of a governance body based on voluntary agreements between local jurisdictions outweighs benefit, even though effectiveness depends also on the geographical adherence to the metropolitan area. Portland, OR and Minneapolis - Saint Paul, MN are two exceptions to the predominant type of metropolitan governance in the US. In fact, the former has a governance body that has the status of full local government and a leadership elected by popular vote. The latter, delivers a wide range of services and benefits from an exceptionally high annual budget of USD 300 per inhabitant - compared to the the USD 3-30 per inh. range usually adopted from the other governance bodies (Ahrend and Schumann, 2014). According to our results, the metropolitan regional government applied to the Minneapolis-St.Paul, MN region featuring a metropolitan tax-base sharing, is expected to increase local productivity.

Chapter 3

The Effect of Immigration on Convergence Dynamics in the US

This paper analyzes the impact of immigration on the dynamics of the cross-sectional distribution of GSP per capita and per worker. To achieve this we combine different approaches: on the one hand, we establish via Instrumental Variable estimation the effect of the inflow of foreign-born workers on output per worker, employment and population; on the other hand, using the Distribution Dynamics approach, we reconstruct the consequences of migration flows on convergence dynamics across US states[1].

[1]Co-authored chapter with Margherita Gerolimetto and Stefano Magrini

3.1 Introduction

The 1990's and the 2000's have witnessed a massive inflow of migrants into the US and this has certainly had a significant redistributive effect within the society. The literature that analyzes this phenomenon has essentially focused on the redistribution across individuals due to variations in wages for workers grouped according to their level of skills. Within a theoretical framework that implies the absence of long-run effects of immigration on productivity, Borjas (2003) and Borjas and Katz (2007) (among many others) assume an infinite elasticity of substitution between immigrant and native workers and find that an inflow of foreign-born population is likely to create a downward pressure on wages of less-educated natives. On the other hand, embracing the same framework but incorporating a positive estimate of the elasticity of substitution between immigrant and native workers with similar characteristics, Card (2009b) and Ottaviano and Peri (2012) find a positive effect on wages for the less-educated as well as for the average natives.

Even if we retain the same theoretical framework, the massive immigration flow experienced in the US is likely to have had redistributive consequences also from a spatial point of view. This could be essentially due to two reasons. Firstly, immigrants tend not to distribute homogeneously across states. According to the American Community Survey data, California is the preferred destination, followed by New York, Texas, Florida, New Jersey and Illinois. Furthermore, the skill distribution for immigrants is characterized by a strong polarization as most of them either acquired a low level of schooling or hold a graduate degree. The heterogeneity in the size and skill composition of the immigration flows across territories is therefore likely to have significant consequences on the magnitude of economic disparities across the territory.

In addition, immigration flows may also have static and dynamic effects on productivity and, through this way, affect economic disparities across space. For example, Ottaviano and Peri (2006) highlight the positive effect of cultural diversity at the urban level on the productivity of native workers, despite differences in the level of education. Hunt and Gauthier-Loiselle (2010) analyze the role of immigration on technological progress as measured by patents and suggest that migrants could positively contribute to the productivity of native researchers at the state level. Finally, Peri (2012) shows that the inflow of foreign-born workers also had a strong positive association with Total Factor Productivity, consistent with the view that more immigrants in a state stimulate its productivity growth.

The general aim of the paper is therefore to identify and quantify the effect of the inflow of foreign-born workers on the evolution of economic disparities among US states.[2] To achieve this, we carry out an analysis of economic convergence in the US from 1970 to 2006 and exploit the information provided by the construction of specific counterfactual scenarios. From a methodological point of view, this task is carried out in two steps. First, we estimate the elasticities of Gross State Product (GSP) per worker, employment and population with respect to employment of foreign-born workers; then, we turn to examine convergence patterns across US states using the Distribution Dynamics approach (Quah, 1993a,b, 1996a,b, 1997). To accomplish this, the coefficients estimated in the previous step are used (in analogy with Cheshire and Magrini, 2000) to derive counterfactual values for per capita GSP levels on hypothetical scenarios that impose *ad hoc* assumptions on the heterogeneity of the growth rate of immigrants across territorial units. Using these counterfactual series, and comparing the results with those derived from the predicted series, makes it possible to evaluate the impact played on the convergence process by immigration flows. In particular, we identify two separate components of immigration flows in the counterfactual scenarios: *i.* international migrations, i.e. flows that have their origin outside of the US territory, and *ii.* secondary migrations, i.e. internal migrations by foreign-born population. In the empirical analysis, we will concentrate on the states: while immigration is regulated at the federal level, chiefly under the rules established in 1952 with the passage of the Immigration and Nationality Act, state governments retain fiscal powers that may affect the direction of the flows.

The main results of the paper indicate that, in line with Peri (2012), immigration spurs employment, population and output per worker growth. In addition, migrations have a very important role in determining the pattern of divergence across states that emerges in the period that ranges from 1970 to 2006; in addition, divergence should not be attributed to the massive inflow of immigrants towards

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[2] The only attempt to analyze the consequences of international migrations on regional convergence we are aware of is the study of Hierro and Maza (2010) on the Spanish experience over the 1996-2005 period. The framework of analysis adopted there is however profoundly different from the one developed in the present paper.

the traditional "gateway" states while a significant, although partial, role might be played by secondary migrations.

The rest of the paper is structured as follows. Section 2 describes the effect that migration flows may have on the distribution of income, Section 3 explains the empirical strategy adopted in the paper, Section 4 presents the empirical analysis and the results, Section 5 concludes.

3.2 The redistributive effects of immigration

Immigration redistributes income across individuals and, due to location choices, across places. The empirical analysis of the consequences of immigration flows has essentially concentrated on the redistribution due to relative changes in wages for individuals grouped on the basis of personal characteristics either comparing outcomes in different cities or states (Card, 2001, 2009a,b; Card and Lewis, 2007; Ottaviano and Peri, 2005, 2006; Peri, 2012) or studying the evolution of outcomes at the national level (Borjas, 2003, 2006; Borjas et al., 1997; Borjas and Katz, 2007; Ottaviano and Peri, 2012).

All these studies share a simple, common framework that relies on the traditional neoclassical explanation of the growth process (Ramsey, 1928; Solow, 1956; Swan, 1956). Suppose aggregate output Y is realized according to

$$Y = AL^{\alpha}K^{1-\alpha} \tag{3.1}$$

where A is total factor productivity growing at a constant exogenous rate μ, K is the stock of physical capital, L is the stock of labor that aggregates different types of workers according to a Constant Elasticity of Substitution (CES) function and $\alpha \in (0, 1)$ is the share of income that remunerates labor. Assuming that the latter is constant, profit maximization under perfect competition implies that the economy approaches a balanced growth path in the steady state in which output per worker (Y/L) and the average wage rate grow at a constant rate equal to $1/\alpha$ times the growth rate of TFP. This, in turn, means that in the long run the average wage does not depend on the level of labor supply and, hence, on immigration. However, despite the absence of effect on the average wage, this framework predicts that immigration could yield effects at a more disaggregated level depending on workers characteristics. In general, immigrant flows exert a downward pressure on wages of workers of similar characteristics and an upward one on wages of workers with different characteristics. In practice, the differences in the estimated effects on the wage of specific groups of workers largely depend on the assumptions made in the operationalization of the CES aggregator with reference to the degree of substitutability among workers with different characteristics. Thus, assuming an infinite elasticity of substitution between immigrant and native workers, Borjas (2003), Borjas and Katz (2007) and studies on this vein, usually report a negative impact on wages of less-educated natives. On the contrary, Ottaviano and Peri (2012) provide an estimate of the substitution elasticities involved in the CES aggregation of workers and, in line with Card (2009a) and Raphael and Smolensky (2009), report a small but significant degree of substitutability between immigrant and native workers with similar characteristics. Based on the entire set of estimated elasticities, Ottaviano and Peri (2012) confirm earlier results by Card (2009a) finding a small but positive effect of immigrant flows on wages of less-educated natives, a positive effect on the average wage of natives and a strong, negative effect on immigrants that entered the country previously. In addition, they stress the importance of distinguishing between partial and total wage effects. In the case of an in-flow of immigrant workers with a given set of characteristics, the partial wage effect represents the direct impact on the wage of native workers with the same characteristics assuming that the labor supply of all other groups stays constant. In contrast, the total wage effect instead quantifies the impact the wage of native workers with the same characteristics allowing for the indirect impacts of immigration in all other skill groups. Hence, it follows that the total wage effect on groups with given characteristics depend on the relative sizes of these groups, on the relative strengths of the impact of immigrants within and across groups, and on the characteristics profile of migrants.

From the above discussion, it follows that, even if we adopt the theoretical framework just highlighted and consequently presume that immigration has no long-run effect on the average real wage, immigration flows could still have important redistributive consequences from a spatial point of view. Actually, workers with different characteristics are distributed rather heterogeneously across space. Similarly, immigrant flows tend to head disproportionally towards a limited number of areas of the country and to be concentrated in certain parts of the skill distribution. It is well known that new migrants tend to choose destinations where they have strong migrant networks, and states with large settled immigrant populations are sometimes called "gateway-states". For instance, based on American Community Survey data, in 2010 about two-thirds (65%) of the total foreign-born population lived in just six states (California, New York, Texas, Florida, New Jersey and Illinois)[3] and over one-fourth (25.4%) lived in California. As for the skills, immigrant flows appear to be concentrated in the upper and lower tails of the distribution of schooling attainment. Immigrants are much more likely than natives to have low levels of schooling. For instance, in 2010 about 32% of immigrants had not completed the equivalent of high-school education, compared with only 11% of natives. At the same time, immigrants are as likely as natives to be highly educated, with 27% of immigrants and 28% of natives having completed a bachelor's degree. In contrast, are underrepresented in the middle of the skill distribution, among workers with high-school or some college education (41% for immigrants, 61% for natives). Given this heterogeneous distribution of migrants across states and across skills, the redistributive effects among different groups of workers found in the recent literature are necessarily accompanied by redistributive effects between different areas of the country.

That aside, the theoretical framework adopted in estimating the impact of immigration on wages explicitly omits any effect, static or dynamic, that these flows might have on productivity.[4] In a couple of cross-city studies focusing on the US, Ottaviano and Peri (2005, 2006) find that cultural diversity, either in terms of variety of workers' mother tongues or in terms of variety of their country of birth, has a net positive effect of on the productivity of natives. They suggest that the effect originates from differences, even at the same level of education, in problem solving, creativity and adaptability between native and foreign-born workers or from the fact that the latter may provide services that are not perfectly substitutable with those of supplied by natives. Similarly, Niebuhr (2010), focusing on a cross-section of German regions, finds evidence favoring the hypothesis that cultural diversity enhances innovation activity. Hunt and Gauthier-Loiselle (2010) study the impact of immigration on technological progress in the US, as measured by patents per capita. In addition to the direct contributions of immigrants to research, they suggest the way in which immigration could favor indirectly innovation is

[3] In the 1960s and 1970s, Massachusetts and Pennsylvania were also "gateway" states.

[4] Ozgen et al. (2010), applying several meta-analytical techniques, find that the overall effect of migration on real per capita income growth is positive, although of limited size.

through positive spillovers originating from immigrants to the benefit of fellow researchers, as well as contributing to the exploitation of scale economies or providing skills that are complimentary to those of natives. Gagliardi (2015) finds that skilled immigration has a positive and significant effect on innovation activity within British local labor markets. Peri (2012) finds that the inflow of foreign-born workers has a strong positive association with TFP growth and that efficiency gains tend to be larger for less educated workers. In particular, the author suggests that boost to the efficiency could arise from a process of reorganization of production within firms in which immigrants specialize in manual-intensive tasks and natives take up communication-intensive ones.

Similarly to what seen before, due to differences across locations in their degree of cultural diversity, attitude towards innovation and organization of the production process as well as in the size and skill composition of the immigration flows, strongly different spatial manifestations are likely to arise. Building on the impacts on real wages described above, these further effects of immigration on productivity are likely to affect the relative economic performance of the different areas of the country, interacting with the underlying convergence or divergence dynamics. The goal of our paper is precisely this: to assess the impact of immigration on convergence among US states by isolating the spatial (static and dynamic) impact of the inflow of immigrant workers on the evolution of state disparities in economic performance.

3.3 The Empirical Strategy

In order to establish the role of international migrations on the dynamics of the cross-sectional distribution of per capita GSP we adopt a two-step strategy:

1. first, drawing extensively on the framework developed by Peri (Peri, 2012; but also Peri and Sparber, 2009), we estimate the impact of international migration on GSP per worker, employment and population;

2. then, we turn to examine convergence patterns across US states using the distribution dynamics approach (Quah, 1993a,b, 1996a,b, 1997). To accomplish this, the coefficients estimated in the previous step are used (in analogy with Cheshire and Magrini, 2000) to derive counterfactual values for GSP

per capita and GSP per worker on hypothetical scenarios that impose *ad hoc* assumptions on the distribution of immigrants flows across territorial units. Using these counterfactual series, and comparing the results to those derived from the predicted series, makes it possible to evaluate the impact played on the convergence process by immigration flows.

3.3.1 Regression analysis

Let us consider the setup of the regression analysis in greater detail. Define the level of output per worker of state s at time t as $\tilde{y}_{st} \equiv Y_{st}/L_{st}$. Taking the log, differentiating with respect to time and rearranging yields

$$\frac{\Delta Y_{st}}{Y_{st}} = \frac{\Delta \tilde{y}_{st}}{\tilde{y}_{st}} + \frac{\Delta L_{st}}{L_{st}} \tag{3.2}$$

which states that total output in a state increases as a consequence of increased employment and increased output per worker.

Similarly, let P_{st} denote the population of state s at time t and define the corresponding level of output per capita as $y_{st} \equiv Y_{st}/P_{st}$ from which log-differenciation with respect to time yields

$$\frac{\Delta y_{st}}{y_{st}} = \frac{\Delta Y_{st}}{Y_{st}} - \frac{\Delta P_{st}}{P_{st}} \tag{3.3}$$

Putting equation (3.2) into (3.3) we then get:

$$\frac{\Delta y_{st}}{y_{st}} = \frac{\Delta \tilde{y}_{st}}{\tilde{y}_{st}} + \frac{\Delta L_{st}}{L_{st}} - \frac{\Delta P_{st}}{P_{st}} \tag{3.4}$$

The decomposition in equation (3.4) is at the basis of the first step of the empirical analysis. In analogy with Peri and Sparber (2009) and Peri (2012), we estimate the impact of immigration by regressing each element of the right-hand side of equation (3.4) against the percentage change in employment due to immigrants. In particular, we estimate

$$\frac{\Delta b_{st}}{b_{st}} = d_t + d_s + \eta_b \frac{\Delta L^F_{st}}{L_{st}} + \epsilon_{st} \tag{3.5}$$

where b is alternatively $\tilde{y}$, L or P, L^F is the number of employed immigrants while d_t and d_s are, respectively, decade and state dummies.

Clearly, as emphasized by Peri and Sparber (2009) and Peri (2012), it is difficult to establish a causal link between immigration and economic outcomes due to simultaneity and omitted variable biases. For this reason, we carry out Instrumental Variable (IV) estimates in which, following the just mentioned authors, we employ several variables as instruments. The first variable, originally devised by Card (2001) and then used in several other studies (Card, 2009b; Peri, 2012; Peri and Sparber, 2009), is the imputed number of immigrants constructed as the weighted average of decade-by-decade nationwide immigrant workers inflow by 10 different origin areas, with weights reflecting their location-specific share in 1960. In addition, we pay some consideration to spatial effects. In actual facts, the location of immigrants is not random as destination depends, among other things, on distance from the entry point. Consequently, we include among the instruments a couple of variables reflecting (the inverse of)[5] distance of a states' center of gravity from entry points for Mexican migrants (interacted with decade dummies) to predict the inflow of workers in decades with larger Mexican immigration.

3.3.2 Counterfactual Scenarios

From the estimated elasticities $\hat{\eta}_P$, $\hat{\eta}_L$ and $\hat{\eta}_{\tilde{y}}$, using the observed values for the explanatory variables in equation (3.5) we then calculate the predicted levels of GSP per worker and GSP per capita. More precisely, to obtain the predicted values we use the values of the percentage change in employment due to immigrants estimated in the first stage of the 2SLS procedure and the observed values for all other variables.

In addition, in analogy with Cheshire and Magrini (2000), we construct some counterfactual scenarios based on different assumptions with respect to the distribution of immigrant workers across states. The first counterfactual scenario emphasizes the effect from traditional "gateway-states" such as California, Florida, Illinois, New Jersey, New York and Texas which continue to be home to large percentages of immigrants. In order to set up such a scenario (hereafter, the "gateways" scenario), in each decade we impose that the shock represented by the inflow of immigrant workers is homogeneously distributed across all states

[5] Peri (2012) also includes distance related variables among the instruments; in that case, however, the variables report the logarithm of distance rather than its inverse as in the present case.

but the 6 “gateways”. In operative terms, to achieve this, for all states but the 6 “gateways”, the (estimated) percentage change in employment due to immigrant workers is set equal to the decade-specific cross-sectional average (net of the shock occurring to the “gateways”).

The second counterfactual scenario attempts to highlight the role of secondary migration. In fact, growth in a state’s foreign-born population occurs through movements from abroad or through foreign-born migrants’ secondary migration from elsewhere in the United States after their initial arrival. Once arrived in a “gateway” state, many movers from abroad then relocate to different areas of the country in response to economic incentives much like other groups (Cadena, 2013; Card and Lewis, 2007). This phenomenon has gained particular importance in recent decades also because, as reported by Perry and Schachter (2003), recent arrivals to the United States had higher mobility rates than foreign-born people who entered before 1980. So, although the six gateway states were still receiving large numbers of immigrants during the 1990s, three of them (California, New York, Illinois) experienced substantial net outmigration that included a sizable foreign-born component during the 1990s and two (California and New York) started to play an important role in the redistribution of the foreign-born population across the United States as the net domestic outmigration rates for the foreign-born exceeded the rates for natives. On the same vein, Bean et al. (2007) report that during this decade there was a substantial out-migration of Mexicans from most traditional Mexican-receiving US states and these flows were heading towards those states experiencing faster economic growth. As a result of these flows, the relative importance of traditional “gateway-states” has visibly declined: while almost three-quarters of immigrants lived in one of the traditional “gateway-states” in 1990, this proportion dropped to 65% by 2010. At the same time, other states have witnessed a rapid increase in their foreign-born population. Focusing on internal migration of the foreign-born, Perry and Schachter (2003) report that the states with the higher rates of net migration during the first half of the 1990s where Nevada (276.0), North Carolina (187.0) and Georgia (178.1). Frey (2002), using Census data on foreign-born residents who arrived in the United States to live prior to 1990, finds that the states that obtained the largest inflows from secondary migration of the foreign-born during the 1990-2000 period where Nevada (72,471), Arizona (60,597), Georgia (59,384) and North Carolina (46,566). Based on these figures, therefore, four states (Nevada, Arizona, Georgia and North Carolina) are identified as the main recipients of secondary migration flows from the 1990s. Consequently, the second countefactual scenario (hereafter, the "secondary migration" scenario) is constructed by imposing, from 1990 onwards, that for all states but the 4 "gainers" from secondary migration flows, the (estimated) percentage change in employment due to immigrants is set equal to the decade-specific cross-sectional average (net of the change faced by the "gainers").

Finally, in the third counterfactual scenario the differential effect of immigration is instead completely neutralized by imposing a homogenous shock across all states by enforcing that the (estimated) percentage change in employment due to immigrants is, for each state, equal to the overall, decade-specific cross-sectional average. Hereafter, this scenario will be referred to as the "all" scenario.

These predicted and counterfactual series represent the inputs for the Distribution Dynamics analysis that will allow to analyze the impact of immigration flows on the dynamics of the cross-sectional distribution of GSP per capita and GSP per worker.

3.3.3 Distribution Dynamics Analysis

The most frequently adopted notion of convergence is β-convergence, whose theoretical foundations lie in the traditional neoclassical growth model originally set out by Solow (1956) and Swan (1956). Technically, as is well known, the key parameter to be empirically estimated is the rate β at which the representative economy approaches its steady-state growth path (Barro and Sala-i Martin, 1991, 1992, 2004). This approach, however, has stimulated the critical attention of many scholars who have emphasized its limitations and proposed alternatives (for an account of this literature see, among others Durlauf et al., 2005; Durlauf and Quah, 1999; Islam, 2003; Magrini, 2004b, 2009; Temple, 1999). In our view, its most important drawback relates to the lack of informative content: concentrating on the behavior of a representative economy, the best this approach can do is to describe how this economy converges to its own steady-state; it is however completely silent on what happens to the entire cross-sectional distribution of economies. For this reason, here we opt for the continuous state-space distribution dynamics approach first introduced by Quah (1996a, 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.

In simple terms, indicate with $\bar{y}_{i,t}$ the level of income (per capita or per worker) of state s at time t relative to the cross-sectional average. Next, denote with $F(\bar{y}_t)$ the distribution of $\bar{y}_t$ and, assuming it admits a density, indicate this density with $f(\bar{y}_t)$. Finally, assume that the dynamics of $F(\bar{y}_t)$, or equivalently of $f(Y\bar{y}_t)$, can be modeled as a first order process. As a result, the density prevailing at time $t+s$ is given by

$$f\left(\bar{y}_{t+s}\right) = \int_{-\infty}^{\infty} f\left(\bar{y}_{t+s}|\bar{y}_t\right)\ f\left(\bar{y}_t\right)\, d\bar{y}_t \tag{3.6}$$

where the stochastic kernel $f(\bar{y}_{t+s}|\bar{y}_t)$ maps the density at time t into the density at time $t+s$. This element is the corner-stone of the approach as its (nonparametric) estimate provides information both on the change in the external shape of the distribution and, more importantly, on the movement of the economies from one part of the distribution to another between time t and time $t+s$. Convergence can hence be analyzed directly from the shape of a plot of the stochastic kernel estimate or, assuming that the process behind (3.6) follows a time homogenous markov process, by comparing the shape of the initial distribution to the stationary (or ergodic) distribution which is the limit of $f(\bar{y})$ as $s \rightarrow \infty$.

Effectively, the stochastic kernel in equation (3.6) is a conditional density function, an estimate of which can be obtained through a kernel density estimator. However, Hyndman et al. (1996) suggest that this popular estimator might have poor bias properties.[6] To clarify this, let $M(\bar{y}_t)$ indicate the mean of the conditional density $f\left(\bar{y}_{t+s}|\bar{y}_t\right)$. As emphasized by Hyndman et al. (1996), the bias of estimate of the conditional density function depends on the bias of estimate of the mean function. Unfortunately, the mean function estimator implicit in the traditional kernel estimator of the conditional density is the local constant estimator which is known to have poor bias properties. Hence, these poor bias properties are carried over onto the conditional density estimate. To overcome this problem, these authors then develop a mean-bias adjustment procedure that entails estimating $M(\bar{y}_t)$ using a smoother characterized by better bias properties and then substitute

[6] The local constant estimator is known to be biased on the boundaries and also in the interior, especially when the mean function is characterized by an evident curvature or simply the scatter plot of the design points is irregular.

this estimate in place of the original one. One such smoother is, for instance, the local linear estimator (Loader, 1999).

Important implications for the analysis could also arise from its spatial dimension. Gerolimetto and Magrini (2016) note that the estimate of $M(\bar{y}_t)$ is in fact an autoregression and emphasize that the asymptotic properties of the adopted smoother are usually based on the assumption that the error terms are zero mean and uncorrelated. However, in the analysis of economic convergence across spatial units, the involved variables are usually characterized by spatial dependence. Within the distribution dynamics approach the issue is typically tackled by adopting a spatial filtering technique before proceeding with the estimates. For example, Basile (2010) fits a spatial autoregressive model and employs residuals for subsequent analysis while Fischer and Stumpner (2008) and Maza et al. (2010) employ a filtering approach based on the local spatial autocorrelation statistic *Gi* developed by Getis and Ord (1992). A strict assumption however underlies this approach: spatial dependence is seen as a nuisance element that should be eliminated in order to avoid the risk of losing the statistical properties of the estimates (Anselin, 1988, 2002). Differently from this view, Gerolimetto and Magrini (2016) think that spatial dependence is often likely to be a substantive element of the process under study and this, in particular, should be the case when studying economic convergence across regional units. Just to give an example, not only it is well known that the level of per capita income in a US state is correlated to the level observed in neighboring states but, as shown by Rey (2001), also the mobility of the states within the cross-sectional distribution of per capita income is significantly affected by the relative position of geographical neighbors within the same distribution. In such instances, spatial dependence appears to embody valuable information on convergence dynamics and adopting a spatial filtering technique represents a controversial strategy (Magrini, 2004b) as it may yield misleading results. To address the issue, therefore, Gerolimetto and Magrini (2016) first develop a two-step nonparametric regression estimator for spatially dependent data that moves from the standard local linear estimator and does not require *a priori* parametric assumptions on spatial dependence as information on its structure is in fact drawn from a nonparametric estimate of the errors spatial covariance matrix. Then, they employ this spatial nonparametric (local linear) estimator in the mean-bias adjustment procedure put forward by Hyndman et al. (1996). In the present paper, we adopt the strategy developed by Gerolimetto and Magrini (2016) and therefore enrich the estimate of the conditional density through an estimate of the mean function that, in addition to Hyndman et al.s' original suggestion, allows also for spatial dependence.

3.4 Empirical Analysis

We adopt states as the territorial unit of analysis. This is done for two reasons. First, while immigration is regulated at the federal level, chiefly under the rules established in 1952 with the passage of the Immigration and Nationality Act, state Governments retain fiscal powers that may affect the direction of the flows. Secondly, as emphasized by Peri and Sparber (2009), the immigrant share of employment varies greatly across US states.[7]

As recalled at the outset, the definition of most variables employed in the regression analysis coincide exactly with those in Peri (2012) as we exploit the dataset included in the downlodable supplementary material of the paper. In line with the analysis conducted there, the period of analysis stretches between 1970 and 2006.[8]

3.4.1 Regression Analysis

The estimated impacts of immigration on employment and labor productivity reported in Table 3.1 are obviously in line with those reported by Peri (Peri, 2012, Table 2, column 1). In particular, we find that the elasticity of employment is just above 1 while the elasticity of income per worker is marginally smaller (0.92).[9] Both effects of immigration appear to be highly statistically significant thus confirming

[7] Borjas (2003) and Borjas and Katz (2007) criticize this choice on the basis that states are open economies and the effects of immigration in one state could spill into others through the migration of natives. Peri and Sparber (2009) however note that there is little evidence in the literature that natives respond to immigration through interstate migration.

[8] Although required data are certainly available for more recent years, we have decided to maintain the original time-horizon essentially because it allows to avoid to contaminate the results with the effects of the Great Recession during which migration flows both from outside and within the US territory declined quite markedly.

[9] The minor differences with the elasticities reported by Peri are essentially due to the fact that, among the instruments, we employ the inverse of distance from the border rather than its logarithm. In addition, we corrected a few data entries relative to Delaware's employment in 1990.

that more immigrants in a state stimulate the growth of both its productivity and employment.

In addition, the last column of Table 3.1 also reports that the impact of immigration on population exceeds 1; as with the other elasticities, also this impact arising from the inflow of migrants appears to be strongly statistically significant.

Finally, Table 3.2 reports the results of a test for spatial autocorrelation in the regression residuals. In particular, the table reports, for each regression and each decade, the p-values of a Moran's I test on the residuals obtained using a 5-nearest neighbor spatial weights matrix. In at least two of the three residual sets, the test does not seem to suggest the presence of particularly severe problems.

3.4.2 Convergence Analysis

Having estimated the elasticities η_P, η_L and $\eta_{\tilde{y}}$, we can now evaluate the impact of immigrant workers on the distribution of GSP per worker and GSP per capita across states.

The output of the empirical analysis of distribution dynamics is essentially a set of pictures: a three-dimensional plot of the estimated stochastic kernel, the corresponding Highest Density Region plot (Hyndman, 1996) in which the vertical strips represent conditional densities for a specific value in the initial year dimension and, for each strip, darker to lighter areas display the 10%, 50% and 90% highest density regions, and a plot comparing the initial distribution with the ergodic one. Each of the figures reported in this paper (Figures 3.1 to 3.4) will then show three such sets: one will report the outcome of the analysis carried out on data predicted through the IV regressions and the other two will depicts the estimates for alternative counterfactual scenarios. The information provided by each set of pictures is then complemented by some statistics on dispersion of the initial and ergodic distributions; these statistics are collected in Tables 3.3 and 3.4.

Before proceeding to the analysis of the figures, a note on the estimate of the stochastic kernel. As anticipated in Section 3.3.3, this estimate is carried out using the procedure developed by Gerolimetto and Magrini (2016) in which the mean function of the conditional density is obtained using a spatial nonparametric estimator. The results of the Moran's I test on the residuals of the estimate of $M(\bar{y}_t)$ that substantiate this choice are reported in Table 3.7. It is clear from this table than with just one exception, all residuals obtained using the traditional nonparametric smoother in the estimate of $M(\bar{y}_t)$ display spatial dependence to a significative extent. In contrast, essentially no signs of spatial dependence are found in the residuals from the estimates produced using the spatial nonparametric estimator.

Figure 3.1 shows three sets of such figures with respect to the evolution of the distribution of income per capita over the 1970-2006 period. To interpret these results, let us start from rightmost set of pictures corresponding to the "all" scenario. As explained in Section 3.3.2, in this scenario we completely neutralize the differential effect of immigration by imposing that, for each state, the (estimated) percentage change in employment due to immigrant workers is equal to the overall, decade-specific cross-sectional average. The comparison between initial and ergodic distributions estimated under this scenario indicates a clear tendency towards persistence: in other words, if we neutralize the differential effect of migrations, the external shape of the cross-sectional distribution remains essentially unaffected. Next, moving to the "gateway" scenario, we can see what happens once the differential effect of immigrant flows directed towards the traditional gateways states is introduced. The comparison between initial and ergodic distributions in the central column of Figure 3.1 suggests that, despite their importance in absolute terms, the flows of immigrant workers directed towards the traditional gateway states modify only marginally the previous results by introducing a modest tendency towards divergence in the cross-sectional distribution. A much stronger tendency towards divergence is instead portrayed in the leftmost set of pictures that correspond to the predicted data. This implies that, once the differential effect of the flows of immigrant workers is entirely considered, cross-sectional disparities in per capita income manifest a marked tendency to increase over the 1970-2006 period. This is confirmed by the statistics on dispersion in Table 3.3: both the variation coefficient and the interquartile range of the ergodic distribution denote a substantial increase with respect to the corresponding values for 1970 distribution on predicted data while no appreciable differences are evident in the two counterfactual scenarios. The results of the two-sample Cramér-von Mises tests[10] shown in Table 3.4 reinforce this conclusion: the null hypothesis that the

[10] The Kolmogorov-Smirnov test is the most commonly adopted test that measures the probability that a chosen univariate dataset is drawn from the same parent population as a second dataset. In particular, the Kolmogorov-Smirnov test is a nonparametric test based on the Kolmogorov-Smirnov

initial and ergodic samples are drawn from the same distribution is safely accepted in both counterfactual scenarios; in constrast the null is strongly reject when the predicted data are used. All in all, therefore, the underlying message is that the flows of immigrant workers greatly contribute to the increase of per capita income disparities across states over the 1970-2006 period; further, this result is not due to the role played by the traditional "gateway" states but rather by the flows directed (or re-directed) to all other states.

We can now move to the analysis of the series on income per worker. As shown in the set of pictures corresponding to the "all" scenario of Figure 3.2, also in the case of income per worker no tendencies to change the cross-sectional distribution are found during the 1970-2006 period once the differential effect of immigration is neutralized. Differently from the case of income per capita, however, once the effects of the flows of immigrant workers are reintroduced in the analysis, either partially (the "gateway" scenario) or fully (using predicted data), no radical changes to the cross-sectional distribution can be noted. In fact, the pictures comparing initial and ergodic distributions, the statistics reported in Table 3.3, as well as the Cramér-von Mises tests reported in Table 3.4, suggest only a quite marginal tendency towards convergence.

As explained in Section 3.3.2, since the 1990s, not only the relative importance of traditional "gateway-states" has visibly declined, but the phenomenon of secondary migration has gained strong momentum. The final part of this analysis is then aimed at ascertaining the contribution of secondary migration of foreign-born workers to the evolution of income disparities across states. Given than this is a recent phenomenon, the analysis will concentrate on the 1990-2006 period.

The rightmost set of pictures in Figure 3.3 confirm also for this shorter period that, once the differential effect of the flows of immigrant workers is neutralized, the dynamics of the cross-sectional distribution of per capita income are characterized essentially by persistence. Once the attention is concentrated on those states that have been the main recipients of re-location flows by foreign-born workers (the central set of pictures corresponding to the secondary scenario), a tendency

statistics that measures the supremum distance between the empirical distribution functions (EDF). However, whenever the EDFs have the same mean values as in the present case, then the EDFs cross each other and the maximum deviation between the distributions is reduced. In such instances, the Cramér-von Mises test that measures the sum of square deviations between the EDFs is a more appropriate choice.

towards an increase of the cross-sectional disparities is detected. This is confirmed by the statistics in Table 3.5 according to which, for instance, the interquartile range of the ergodic distribution increases by 0.0076 with respect to its initial value, an increase of about 33%; further confirmation of this increase in disparities also comes from the Cramér-von Mises test (Table 3.6) according to which we can safely reject the null that the 1990 and ergodic samples come from the same reference distribution. An even more radical increase in disparities is then found when the impact of all flows of immigrant workers is considered using the predicted data. In this case, the shape of the ergodic distribution describes a sharp raise in spatial disparities with an increase of 0.0214 of the interquartile range from its 1990 value (Table 3.5), a value that corresponds to an almost 93% increase, while the Cramér-von Mises statistic increases to 11.8 (Table 3.6). In addition, the comparison between the distributions also suggests the emergence of a pattern of club convergence given the evident bimodality present in the shape of the ergodic.

Moving to the series on income per worker, the picture that emerges from the analysis in the “all” scenario reported in Figure 3.4 is, once more, one of absolute persistence: neutralizing the differential effect of immigrant workers’ flows leads to an ergodic distribution that is almost completely coincident to the one that refers to 1990. Once the effect of secondary migration is allowed in again (the central set of pictures), a modest increase in disparities can be noted with an ergodic distribution characterized by an almost 30% increase of the interquartile range with respect to the initial (Table 3.5); according to the Cramér-von Mises test (Table 3.6), the null hypothesis can be rejected at the 10% significance level only. As in the case of income per capita, also for income per worker disparities increase much more radically if the impact of all flows of immigrant workers is included: the ergodic distribution is far less peaked than the initial, the interquartile range increases by 60% and the Cramér-von Mises statistic raises significantly.

The overall picture that emerges from the analysis conducted in this paper can be summarized as follows. All in all, disparities across states manifest a clear tendency to increase over the 1970-2006 period. This is true both using income per capita (Figure 3.1, “predicted” case) and income per worker (Figure 3.3, “predicted” case) data; this tendency is more marked for income per capita, and becomes stronger in the latter part of the considered period (Figures 3.2 and 3.4). In addition, the analysis suggests that this tendency towards divergence cannot be attributed to the role played by the traditional "gateway" states ("gateway" scenarios of Figures 3.1 and 3.3). Finally, secondary migration instead appears to provide a modest contribution to the divergence pattern ("secondary migration" scenarios of Figures 3.2 and 3.4).

3.5 Conclusions

It is a well known fact that immigrant flows have important redistributive effects across individuals. However, strongly different spatial manifestations are also likely to arise due to differences across locations in the composition of the labor supply, attitude towards innovation, cultural diversity and organization of the production process as well as in the size and skill composition of the immigration flows. This paper has therefore analyzed the consequences of the recent massive inflow of foreign-born population into the US on the evolution of income disparities across states.

First of all, we find evidence in favor of immigration spurring employment, population and output per worker growth, as the estimated elasticities are close to 1. This is in line with previous results by Peri (2012).

For what concerns the analysis of convergence dynamics, in general terms we find a tendency for state levels of both income per capita and income per worker to diverge over the analyzed period. In particular, this tendency appears to be stronger for the former variable and for the 1990-2006 period.

The analysis of counterfactual scenarios clearly shows that the inflow of migrant workers played a fundamental role in these dynamics: neutralizing the differential effect of immigrant workers' flows almost completely eliminates the tendency towards divergence. In addition, the other findings from the counterfactual scenarios indicate that the increase in spatial economic disparities cannot be attributed to the inflow of migrants into the traditional "gateways", while a contribution, although partial, is provided by secondary migration of foreign-born migrants after their initial arrival in the United States, a phenomenon that has gained particular importance in last few decades also because recent arrivals to the United States have higher mobility than earlier ones.

The possible implications of the latter results are of interest. The fact that secondary migrations contribute (although partially) to the divergence process and that, as noted by Cadena (2013) and Card and Lewis (2007), immigrants relocate to different areas of the country in response to economic incentives much like other groups seems to suggests that in recent decades inter-state migrations have not played a mitigating role in the evolution of spatial economic disparities.

Tables

Table 3.1: 2SLS Estimates of the Impact of Immigration

	GSP per worker	**Employment**	**Population**
Coefficient	0.9244	1.0387	1.1136
s.e.	0.1641	0.2722	0.1399
p-value	0.00	0.00	0.00
Over Identification	8.10	12.22	15.74
(p) Over Identification	*0.42*	*0.14*	*0.05*
Under Identification	18.65	18.65	18.65
(p) Under Identification	*0.02*	*0.02*	*0.02*
Weak Identification	80.56	80.65	80.65
First-Stage F-test	108.96	108.96	108.96

Note: The explanatory variable is the percentage change in employment due to immigrants. Each cell is the result of a separate regression. The units of observations are U.S. states (plus DC) in the period 1970-2006. Each regression includes state fixed effects and year fixed effects. Estimation method 2SLS with standard errors heteroskedasticity robust and clustered by state.

Table 3.2: Moran's I p-values on Regression Residuals

	GSP per worker	**Employment**	**Population**
1960-1970	0.00	0.32	0.00
1970-1980	0.03	0.00	0.00
1980-1990	0.00	0.00	0.01
1990-2000	0.95	0.05	0.00
2000-2006	0.22	0.08	0.00

Note: Moran's I test carried out using a 5-nearest neighbor spatial weight matrix. At the 1% confidence level, in at least two of the three residual sets (GSP per worker and Employment), the test does not seem to suggest the presence of severe problems.

Table 3.3: Distribution Dynamics 1970-2006 – summary of statistics

	predicted		**counterfactual gateways**		**counterfactual all**	
GSP per capita	CV	IR	CV	IR	CV	IR
ergodic	0.0315	0.0492	0.0204	0.0303	0.0189	0.0266
Δ from 1970	0.0092	0.0223	0.0002	0.0043	-0.0013	0.0006
GSP per worker	CV	IR	CV	IR	CV	IR
ergodic	0.018	0.0265	0.0177	0.0249	0.0161	0.0219
Δ from 1970	0.0018	0.0043	0.0014	0.0027	-0.0002	-0.0003

Note: IC stands for Interquartile Range, CV stands for Coefficient of Variation.

Table 3.4: Distribution Dynamics 1970-2006 – Cramér-von Mises test

	predicted		**counterfactual gateways**		**counterfactual all**	
	statistic	p-value	statistic	p-value	statistic	p-value
GSP per capita	2.3173	0.0000	0.0929	0.6684	0.0054	1.0000
GSP per worker	0.2339	0.2187	0.2738	0.1656	0.1348	0.4682

Table 3.5: Distribution Dynamics 1990-2006 – summary of statistics

	predicted		**counterfactual secondary migration**		**counterfactual all**	
GSP per capita	CV	IR	CV	IR	CV	IR
ergodic	0.0249	0.0445	0.0201	0.0307	0.0192	0.0272
Δ from 1990	0.0077	0.0214	0.0030	0.0076	0.0000	0.0032
GSP per worker	CV	IR	CV	IR	CV	IR
ergodic	0.0169	0.0291	0.0147	0.0233	0.0135	0.0201
Δ from 1990	0.0038	0.0109	0.0019	0.0053	0.0006	0.0021

Note: IC stands for Interquartile Range, CV stands for Coefficient of Variation.

Table 3.6: Distribution Dynamics 1990-2006 – Cramér-von Mises test

	predicted		**counterfactual secondary migration**		**counterfactual all**	
	statistic	p-value	statistic	p-value	statistic	p-value
GSP per capita	11.8003	0.0000	1.1054	0.0020	0.0528	0.9168
GSP per worker	4.0541	0.0000	0.3395	0.1072	0.0644	0.8461

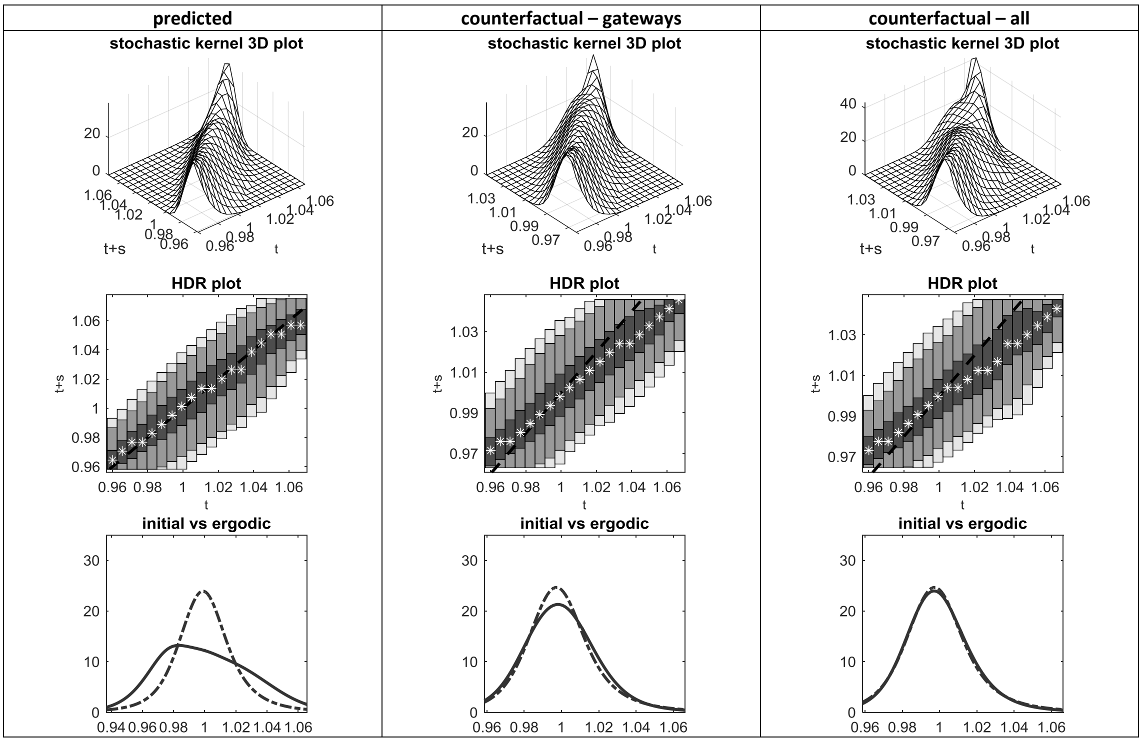
Table 3.7: Moran's I p-values on Data and Nonparametric Regression Residuals

	GSP per capita	**GSP per worker**
Data		
1970 (predicted)	0.00	0.00
1990 (predicted)	0.00	0.00
2006 (predicted)	0.01	0.03
2006 (counterfactual - gateways)	0.01	0.16
2006 (counterfactual - all)	0.00	0.06
Mean function estimate - nonparametric regression residuals		
1970 (predicted) - 2006 (predicted)	0.00	0.00
1970 (predicted) - 2006 (counterfactual - gateways)	0.00	0.00
1970 (predicted) - 2006 (counterfactual - all)	0.00	0.00
1990 (predicted) - 2006 (predicted)	0.00	0.00
1990 (predicted) - 2006 (counterfactual - second migration)	0.30	0.18
1990 (predicted) - 2006 (counterfactual - all)	0.00	0.01
Mean function estimate - spatial nonparametric regression residuals		
1970 (predicted) - 2006 (predicted)	0.47	0.97
1970 (predicted) - 2006 (counterfactual - gateways)	0.28	0.34
1970 (predicted) - 2006 (counterfactual - all)	0.10	0.26
1990 (predicted) - 2006 (predicted)	0.19	0.52
1990 (predicted) - 2006 (counterfactual - second migration)	0.25	0.83
1990 (predicted) - 2006 (counterfactual - all)	0.01	0.21

Note: Moran's I test carried out using a 5-nearest neighbor spatial weight matrix.

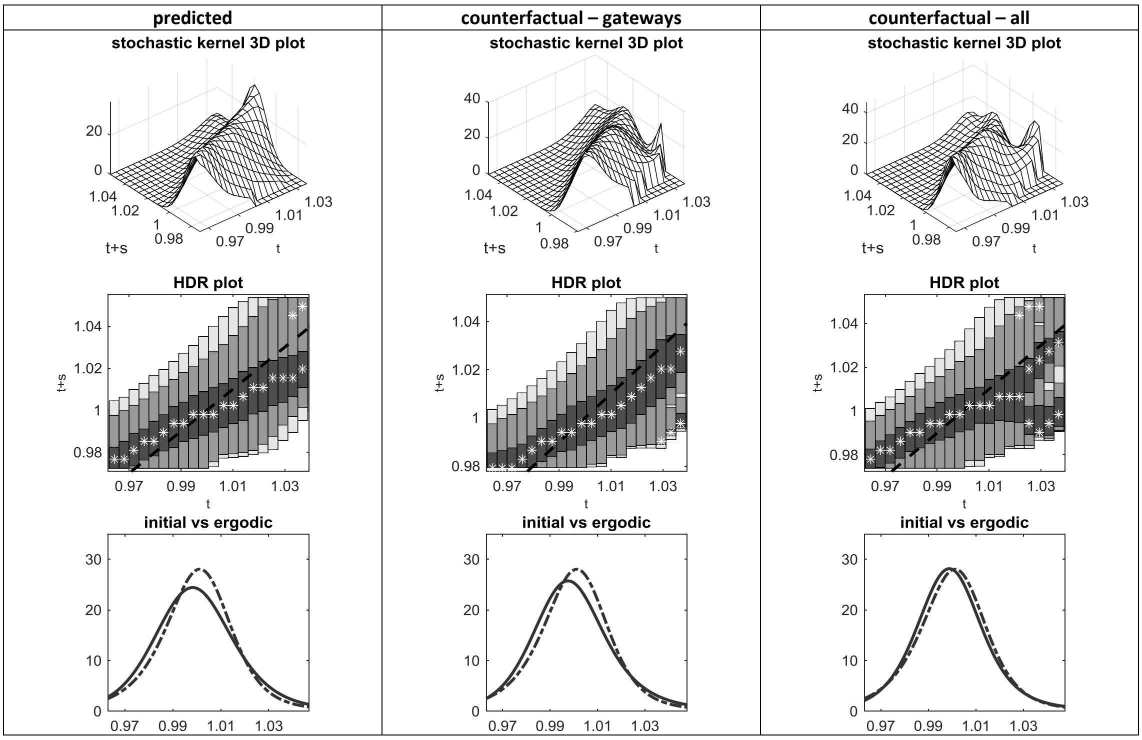
Figures

Figure 3.1: Distribution Dynamics of GSP per capita – 1970-2006



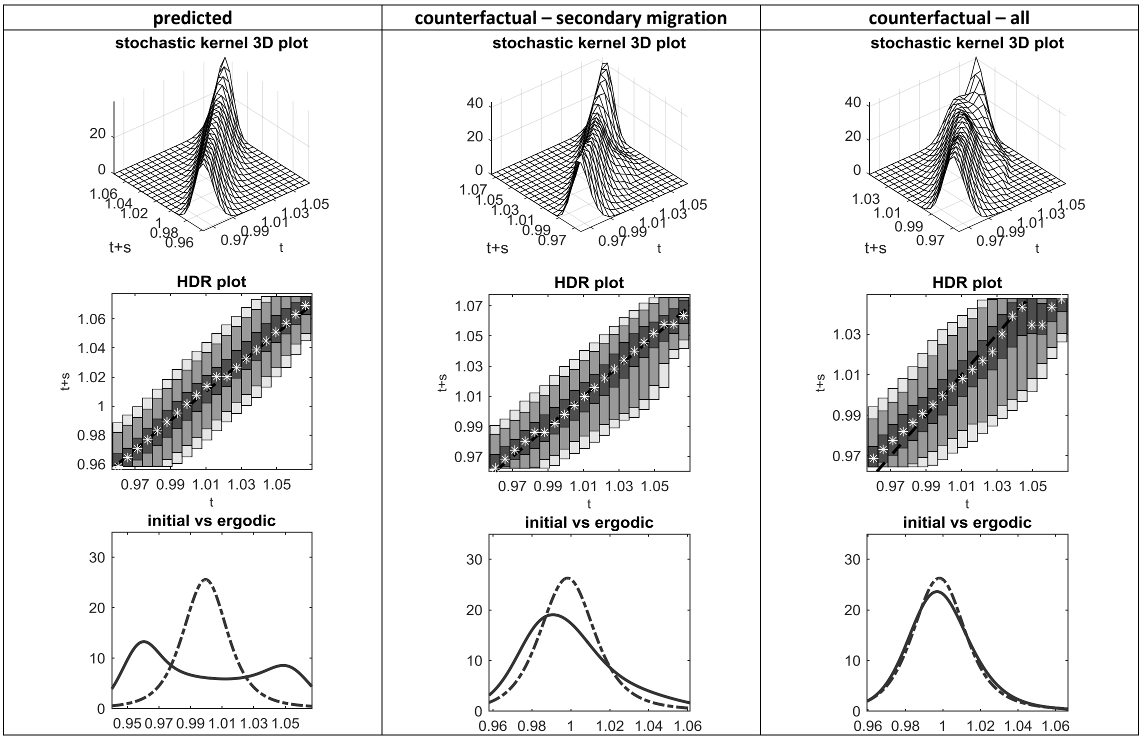
Notes: Estimates use an adaptive bandwidth (span = 0.7) based on a cross-validation minimization in the initial year dimension, a cross-validation minimization bandwidth in the final year dimension and a Gaussian kernel. Mean bias adjustment is obtained via the SNP (local linear) estimator with a cross-validation minimization bandwidth. In contour and highest density region (HDR) plots, the dashed line represents the main diagonal, the asterisk the modes. In the comparison between distributions, the dashed line represents the initial year and the continuous line represents the ergodic.

Figure 3.2: Distribution dynamics of GSP per worker – 1970-2006



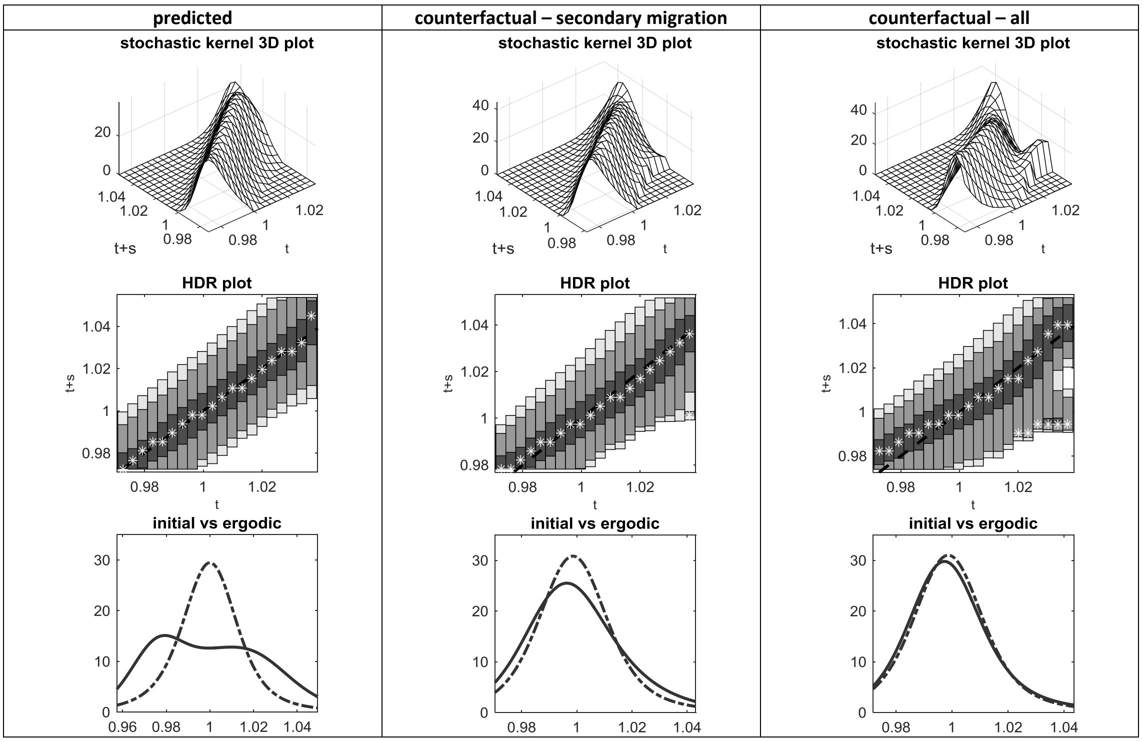
Notes: Estimates use an adaptive bandwidth (span = 0.7) based on a cross-validation minimization in the initial year dimension, a cross-validation minimization bandwidth in the final year dimension and a Gaussian kernel. Mean bias adjustment is obtained via the SNP (local linear) estimator with a cross-validation minimization bandwidth. In contour and highest density region (HDR) plots, the dashed line represents the main diagonal, the asterisk the modes. In the comparison between distributions, the dashed line represents the initial year and the continuous line represents the ergodic.

Figure 3.3: Distribution dynamics of GSP per capita – 1990-2006



Notes: Estimates use an adaptive bandwidth (span = 0.7) based on a cross-validation minimization in the initial year dimension, a cross-validation minimization bandwidth in the final year dimension and a Gaussian kernel. Mean bias adjustment is obtained via the SNP (local linear) estimator with a cross-validation minimization bandwidth. In contour and highest density region (HDR) plots, the dashed line represents the main diagonal, the asterisk the modes. In the comparison between distributions, the dashed line represents the initial year and the continuous line represents the ergodic.

Figure 3.4: Distribution dynamics of GSP per worker – 1990-2006



Notes: Estimates use an adaptive bandwidth (span = 0.7) based on a cross-validation minimization in the initial year dimension, a cross-validation minimization bandwidth in the final year dimension and a Gaussian kernel. Mean bias adjustment is obtained via the SNP (local linear) estimator with a cross-validation minimization bandwidth. In contour and highest density region (HDR) plots, the dashed line represents the main diagonal, the asterisk the modes. In the comparison between distributions, the dashed line represents the initial year and the continuous line represents the ergodic.

Appendix

Figure A1: Spatial evolution of Atlanta, GA metropolitan statistical area

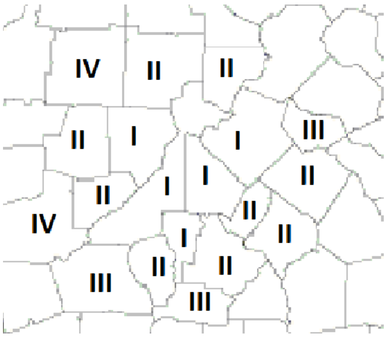


Figure A1 shows how the metropolitan area of Atlanta, GA has evolved over time. The nucleus of five counties marked with **I** refers to the 1960 definition, then in the 1970 the metropolitan area gas gained 10 counties, in 1990 other three and finally, in 2000 Atlanta metropolitan area arrived at twenty counties.

Figure A2: Map of the MSAs included in the analysis

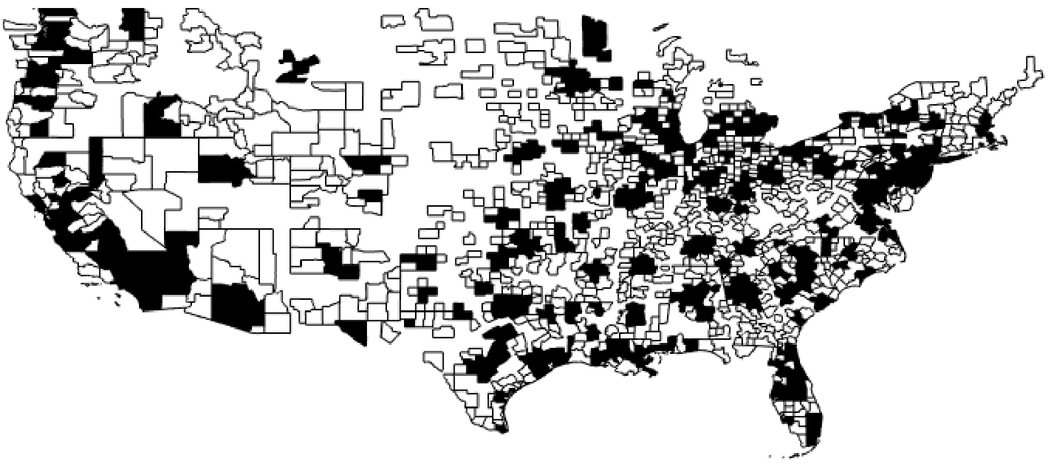
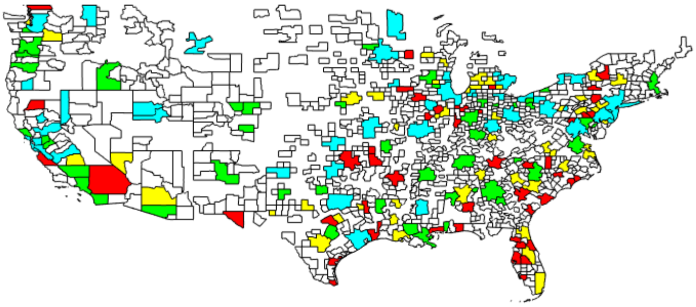
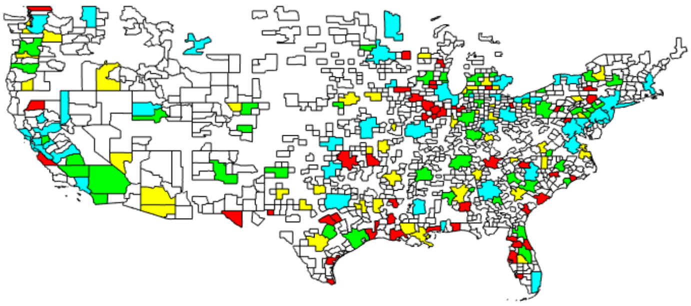


Figure A3: Estimated local productivity by MSA: 1980



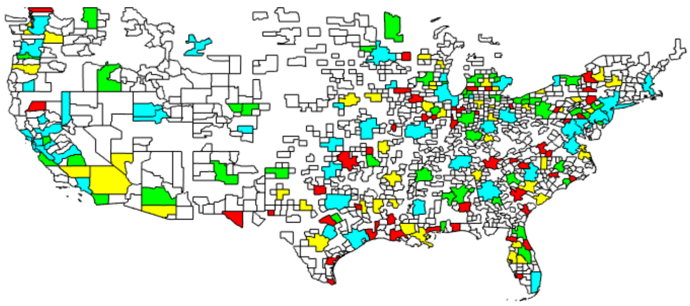
Legend: MSAs with estimated values below the first quartile are in Red, between the first and the second quartile in Yellow, above the median and below the third quartile in Green, above the third quartile in Light Blue.

Figure A4: Estimated local productivity by MSA: 1990



Legend: MSAs with estimated values below the first quartile are in Red, between the first and the second quartile in Yellow, above the median and below the third quartile in Green, above the third quartile in Light Blue.

Figure A5: Estimated local productivity by MSA: 2000.



Legend: MSAs with estimated values below the first quartile are in Red, between the first and the second quartile in Yellow, above the median and below the third quartile in Green, above the third quartile in Light Blue.

Table A1: Metropolitan Areas Definition

	Absolute Values			Percentage Change		
Density	1980	1990	2000	1980	1990	2000
1980	*310.5* *(477.9)*	339.6 (500.7)	380.9 (546.6)	0.00% (0.0%)	1.46% (1.7%)	8.72% (2.7%)
1990	305.5 (470.2)	*334.7* *(492.5)*	375.1 (537.3)	-1.63% (-1.7%)	0.00% (0.0%)	7.07% (0.9%)
2000	285.9 (466.5)	312.6 (488.3)	*350.4* *(532.4)*	-8.60% (-2.4%)	-7.06% (-0.9%)	0.00% (0.0%)
Land	1980	1990	2000	1980	1990	2000
1980	*2471.6* *(2549.4)*	2471.6 (2549.4)	2471.6 (2549.4)	0.00% (0.0%)	-1.38% (0.2%)	-16.91% (-33.5%)
1990	2508.6 (2544.5)	*2506.2* *(2543.6)*	2508.6 (2544.5)	-1.48% (-1.5%)	0.00% (0.0%)	-15.67% (-33.6%)
2000	2974.5 (3832.1)	2974.5 (3832.1)	*2974.5* *(3832.1)*	16.91% (33.47%)	15.75% (33.63%)	0.00% (0.0%)
Fragmentation	1980	1990	2000	1980	1990	2000
1980	*0.660* *(0.41)*	0.609 (0.40)	0.548 (0.38)	0.00% (0.0%)	0.88% (8.7%)	-6.44% (-0.7%)
1990	0.654 (0.38)	*0.603* *(0.37)*	0.543 (0.35)	-0.89% (-9.3%)	0.00% (0.0%)	-7.26% (-8.7%)
2000	0.710 (0.41)	0.653 (0.40)	*0.585* *(0.38)*	7.13% (0.9%)	7.59% (8.8%)	0.00% (0.0%)
Dominance	1980	1990	2000	1980	1990	2000
1980	*0.380* *(0.185)*	0.370 (0.187)	0.358 (0.187)	0.00% (0.0%)	0.59% (-1.66%)	4.32% (0.39%)
1990	0.378 (0.189)	*0.367* *(0.191)*	0.356 (0.190)	-0.59% (1.87%)	0.00% (0.0%)	3.72% (2.08%)
2000	0.365 (0.185)	0.355 (0.186)	*0.343* *(0.186)*	-4.06% (-0.20%)	-3.62% (-2.21%)	0.00% (0.0%)

Mean of Density, Land Area, Fragmentation and Dominance according to the approach adopted. Standard deviations in parenthesis. Rows reports the year of definition of the metropolitan area, according to the OMB official bulletins. Columns are the years to which the observations refer. By reading on the rows, the values are those corresponding to the *constant area approach*, while the values corresponding to the *floating area approach* (in italic) may be read on the principal diagonal. Corresponding percentage change with respect to the latter approach on the last three columns.

Table A2: Second Stage Variables Description

Variable Name	**Description**	**Sources of the Data**
Wage Premium	MSA fixed-effect derived from the First Stage	Integrated Public Use Microdata Series (IPUMS) and authors' elaborations
Density	Population density of the MSA[a] inh/km^2 (natural logarithm)	Bureau of Economic Analysis
Land	Land of the MSA[a] in km^2 (natural logarithm)	Census of Governments - Government Organization - County Area Counts (1977, 1987, 1997)
City Land	Land of the central city in km^2 (natural logarithm)	Census of Governments Gazzeettee 1980, 1990, 2000
Fragmentation	Number of municipalities[a] (natural logarithm)	Census of Governments - Government Organization - County Area Counts (1977, 1987, 1997)
Dominance	Share of population living in the central city in percentage terms	National Historical Geographic Information System / Bureau of Economic Analysis (1980, 1990, 2000)
Special Districts	Number of special districts[a] (natural logarithm)	Census of Governments - Government Organization - County Area Counts (1977, 1987, 1997)
MPOs	Dummy=1 if a Metro Planning Organization covers a significant part of the MSA	National Association of Regional Councils
COGs	Dummy=1 if a Council of Government covers a significant part of the MSA	National Association of Regional Councils
Geographic Adherence	Dummy=1 if the Council of Government is geographically adherent to the MSA	Office of Management and Budget and authors' elaborations
Market Potential	Sum of population density in neighbouring[a] MSA discounted by distance	Bureau of Economic Analysis and authors' elaborations
State Centralization Index	Index of state centralization based on the services delivered by the state, the financial responsibility of the state and state government personnel	Stephens (1997) as calculated for 1995
General Purpose[b]	Dummy=1 if a Metro Planning Organization has strong general purpose governance structures	National Association of Regional Councils

[a] Data at the county level, then aggregated at the metropolitan level according to the delineations provided by the Office of Management and Budget (OMB, 1980-1990-2000)

[b] There are only two MPOs, i.e. the Twin Cities' Metropolitan Council and Portland's Metro, that resemble a full-fledged regional system necessary to integrate land use, transportation, housing and environmental policy on a metropolitan scale.

Table A3: Descriptive Evidences

MSA	Wage Premium	Population	Fragmentation	Dominance	Governance Body
Los Angeles, CA	0.58	9,538,191	88	0.39	Yes
New York, NY	0.96	9,326,888	52	0.86	Yes
San Francisco, CA	0.86	4,135,875	88	0.19	Yes
Atlanta, GA	0.64	4,049,569	105	0.10	Yes
St. Louis, MO	0.51	2,629,933	233	0.13	Yes
Seattle, WA	0.70	2,420,080	56	0.23	Yes
San Jose, CA	1.00	1,684,947	15	0.53	Yes
Sacramento, CA	0.58	1,638,114	13	0.25	No

Data refer to the year 2000. Wage Premia as estimated in the I Stage, normalized with respect to the mean. *Fragmentation* measures the number of municipalities in the Metropolitan Statistical Area, *Dominance* indicates the share of people living in the central city with respect to the whole metropolitan population.

Table A4: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis
Wage Premium	0.733	0.089	0.496	1.067	0.33	3.21
Density	4.479	0.813	2.41	7.842	0.25	4.20
Land	8.529	0.763	6.385	11.541	0.24	3.51
City Land	3.865	1.017	1.334	6.633	0.20	2.84
Fragmentation	3.146	0.893	1.317	5.75	0.33	2.91
Dominance	0.36	0.189	0.058	0.915	0.75	3.03
Special Districts	3.595	1.091	0	6.544	-0.14	3.37
SCI	3.989	0.098	3.793	4.264	-0.86	2.76
MPOs	0.516	0.500	0	1		
COGs	0.582	0.494	0	1		
Geographic Adherence	0.108	0.311	0	1		
General Purpose	0.011	0.104	0	1		

Table A5: List of Metropolitan Statistical Areas with corresponding Council of Government and/or Metropolitan Planning Organization

Metropolitan Area	**COGs**	**MPOs**
Abilene, TX	West Central Texas Council of Governments	Abilene Metropolitan Planning Organization
Akron, OH		Akron Metropolitan Area Transportation Study
Albany-Schenectady-Troy, NY	Capital Region Regional Economic Development Council	Capital District Transportation Committee
Albuquerque, NM	Mid Region Council of Governments	
Alexandria, LA		Alexandria-Pineville Metropolitan Planning Organization
Allentown-Bethlehem-Easton, PA/MA		
Altoona, PA	Southern Alleghenies Planning and Development Commission	Blair County Metropolitan Planning Organization
Amarillo, TX	Panhandle Regional Planning Commission	Amarillo Metropolitan Planning Organization
Ann Arbor, MI	Southeast Michigan Council of Governments	
Anniston, AL	East Alabama Regional Planning and Development Commission	Calhoun Metropolitan Planning Organization
Appleton-Oshkosh-Neenah, WI	East Central Wisconsin Regional Planning Commission	Appleton/Fox Cities MPO
Atlanta, GA	Atlanta Regional Commission	
Atlantic City, NJ		South Jersey Transportation Planning Organization
Augusta-Aiken, GA/SC	Central Savannah River Area Regional Development Center	Augusta-Richmond County Planning Commission
Austin, TX	Capital Area Council of Governments	
Bakersfield, CA	Kern Council of Governments	
Baltimore, MD		Baltimore Metropolitan Council
Baton Rouge, LA	Capital Regional Planning Commission	
Beaumont-Port Arthur-Orange, TX	South East Texas Regional Planning Commission	
Bellingham, WA	Whatcom Council of Governments	
Benton Harbor, MI		
Billings, MT		Billings-Yellowstone County Metropolitan Planning Organization
Biloxi-Gulport, MS	Gulf Regional Planning Commission	
Binghamton, NY	Southern Tier Regional Economic Development Council	Binghamton Metropolitan Transportation Study
Birmingham, AL		Regional Planning Commission of Greater Birmingham
Bloomington-Normal, IL		McLean County Regional Planning Commission
Boise City, ID	Community Planning Association of Southwest Idaho	
Boston, MA		Boston Region MPO
Bremerton, WA	Puget Sound Regional Council	
Brownsville-Harlingen, TX	Lower Rio Grande Development Council	Brownsville MPO
Buffalo-Niagara Falls, NY	Western New York Regional Economic Development Council	Greater Buffalo-Niagara Regional Transportation Council
Canton, OH		
Cedar Rapids, IA	Iowa Northland Regional Council of Governments	
Champaign-Urbana-Rantoul, IL		Champaign County Regional Planning Commission
Charleston, SC	Berkeley-Charleston-Dorchester Council of Governments	Charleston Area Transportation Study
Charlotte-Gaston-Rock Hill, NC/SC	Centralina Council of Governments	Charlotte Regional Transportation Planning Organization
Chattanooga, TN/GA	Southeast Tennessee Development District	Chattanooga-Hamilton County Regional Planning Agency
Chicago, IL		Chicago Metropolitan Agency for Planning
Chico, CA	Butte County Association of Governments	
Cincinatti-Hamilton, OH/KY/IN	OKI (Ohio-Kentucky-Indiana) Regional Council of Governments	Cincinnati-Northern Kentucky MPO
Cleveland, OH		Northeast Ohio Areawide Coordinating Agency
Colorado Springs, CO		
Columbia, MO	Mid-Missouri Regional Planning Commission	Columbia Area Transportation Study Organization
Columbia, SC	Central Midlands Council of Governments	
Columbus, OH	Mid-Ohio Regional Planning Commission	

continued

continued

Metropolitan Area	COGs	MPOs
Corpus Christi, TX	Coastal Bend Council of Governments	Corpus Christi MPO
Dallas, TX	North Central Texas Council of Governments	
Danville, VA	West Piedmont Planning District	Danville MPO
Davenport-Moline-Rock Island, IA/IL		
Dayton-Sprinfield, OH		
Daytona Beach, FL	East Central Florida Regional Planning Council	Volusia MPO
Decatur, IL		Decatur Urbanized Area Transportation Study
Des Moines, IA		Des Moines MPO
Detroit, MI	Southeast Michigan Council of Governments	
Duluth-Superior, MN/WI		Duluth-Superior Metropolitan Interstate Council
Eau Claire, WI		
El Paso, TX	Rio Grande Council of Governments	El Paso MPO
Elkhart-Goshen, IN		Michiana Area Council of Governments
Erie, PA	Northwest Commission	Erie Area Transportation Study MPO
Eugene-Sprinfield, OR	Lane Council of Governments	
Fayetteville, NC	Mid-Carolina Council of Governments	Fayetteville Area MPO
Fayetteville-Springdale, AR		Northwest Arkansas Regional Planning Commission
Flint, MI		
Fort Collin-Loveland, CO		North Front Range Transportation and Air Quality Planning Council
Fort Lauderdale-Hollywood-Pompano Beach, FL	South Florida Regional Planning Council	Broward County MPO
Fort Myers-Cape Coral FL	Southwest Florida Regional Planning Council	Lee County MPO
Fort Wayne, IN	Northeastern Indiana Regional Coordinating Council	
Fresno, CA	Fresno Council of Governments	
Gainesville, FL	North Central Florida Regional Planning Council	Gainsville Metropolitan Transportation Planning Organization
Grand Rapids, MI		
Greeley, CO		
Greensboro-Winston-Salem-Highpoint, NC	Piedmont Triad Council of Governments	Greensboro Urban Area MPO
Greenville-Spartanburg-Anderson, SC	South Carolina Appalachian Council of Governments	Greenville-Pickens Area Transportation Study
Hagerstown, MD		Hagerstown/Eastern Panhandle MPO
Harrisburg-Leban-Carlisle, PA	Capital Region Council of Governments	Harrisburg Area Transportation Study
Hickory-Morgantown, NC	Western Piedmont Council of Governments	Greater Hickory MPO
Houston, TX	Houston-Galveston Area Council	
Indianapolis, IN		Indianapolis MPO
Jackson, MI		
Jackson, MS	Central Mississippi Planning and Development District	
Jacksonville, FL	Northeast Florida Regional Planning Council	First Coast MPO
Jacksonville, NC	Eastern Carolina Council	Jacksonville Urban Area MPO
Janesville-Beloit, WI		Janesville MPO
Johnson-Kinsport-Bristol, TN/VA	First Tennessee Development District	Johnson City Metropolitan Transportation Planning Organization
Johnstown, PA	Southern Alleghenies Planning and Development Commission	Johnstown Area Transportation Study
Joplin, MO		
Kalamazoo, MI		
Kansas City, MO/KS	Mid-America Regional Council	
Kileen-Temple, TX	Central Texas Council of Governments	Killeen-Temple MPO
Knoxville, TN	East Tennessee Development District	Knoxville Regional Transportation Planning Organization
Lafayette, LA		Lafayette MPO

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Metropolitan Area	COGs	MPOs
Lafayette, IN		Tippecanoe County Area Plan Commission
Lakeland-Winter Haven, FL	Central Florida Regional Planning Council	
Lancaster, PA		
Lansing-East Lansing, MI		
Las Vegas, NV		Regional Transportation Commission of Southern Nevada
Lexington-Fayette, KY		Lexington Area MPO
Lima, OH		
Lincoln, NE		Lincoln MPO
Little Rock-North Little Rock, AR		Metroplan - Little Rock
Longview-Marshall, TX	East Texas Council of Governments	Longview MPO
Los Angeles-Long Beach, CA	Southern California Association of Governments	
Louisville, KY/IN	Kentuckiana Regional Planning & Development Agency	
Lubbock, TX	South Plains Association of Governments	Lubbock MPO
Macon, GA	Middle Georgia Regional Development Center	Macon-Bibb County Planning & Zoning
Madison, WI	Capital Area Regional Planning Commission	Madison Area Transportation Planning Board
Mansfield, OH		
McAllen-Edinburg-Mission, TX	Lower Rio Grande Development Council	
Medford-Ashland, OR	Rogue Valley Council of Governments	
Memphis, TN/AR/MS	Memphis MPO	Memphis MPO
Milwaukee-Waukesha, WI	Southeastern Wisconsin Regional Planning Commission	
Minneapolis-St. Paul, MN		Metropolitan Council
Mobile, AL	South Alabama Regional Planning Commission	
Modesto, CA		
Monroe, LA	Ouachata Council of Governments	
Montgomery, AL	Central Alabama Regional Planning and Development Commission	Montgomery Area MPO
Muncie, IN		Delaware-Muncie Metropolitan Plan Commission
Nashville, TN	Greater Nashville Regional Council	Nashville Area MPO
New Orleans, LA	New Orleans Regional Planning Commission	
New York, NY	New York City Regional Economic Development Council	New York Metropolitan Transportation Council
Norfolk-Virginia Beach-Newport News, VA	Hampton Roads Planning District Commission	
Ocala, FL	North Central Florida Regional Planning Council	Ocala/Marion County Transportation Planning Organization
Odessa, TX	Permian Basin Regional Planning Commission	Midland-Odessa Transportation Organization
Oklahoma City, OK	Association of Central Oklahoma Governments	
Olympia, WA		
Omaha, NE/IA	Metropolitan Area Planning Agency (Omaha-Council Bluffs)	
Orlando, FL	East Central Florida Regional Planning Council	Metroplan Orlando
Pensacola, FL	West Florida Regional Planning Council	Pensacola MPO
Peoria, IL	Tri-County Regional Planning Commission	
Philadelphia, PA/NJ	Delaware Valley Regional Planning Commission	
Phoenix-Mesa, AZ	Maricopa Association of Governments	
Pittsburgh, PA	Southwestern Pennsylvania Commission	
Portland-Vancouver, OR/WA		Portland Area Comprehensive Transportation System (METRO)
Provo-Orem, UT	Mountainland Association of Governments	
Racine, WI	Southeastern Wisconsin Regional Planning Commission	
Raleigh-Durham, NC	Triangle J Council of Governments	
Reading, PA		

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Metropolitan Area	COGs	MPOs
Redding, CA		Shasta County Regional Transportation Planning Agency
Reno, NV		Washoe County Regional Transportation Commission
Richmond-Petersburg, VA	Richmond Regional Planning District Commission	
Riverside-San Bernadino, CA		
Roanoke, VA	Roanoke Valley-Alleghany Regional Commission	
Rochester, NY	Finger Lakes Regional Economic Development Council	
Rockford, Il		
Sacramento, CA		
Saginaw-Bay City-Midland, MI		Saginaw County Metropolitan Planning Commission
St. Cloud, MN		St. Cloud Area Planning Organization
St. Louis, MO/IL	East-West Gateway Council of Governments	
Salem, OR	Mid-Willamette Valley Council of Governments	Salem-Keizer Area MPO
Salinas-Sea Side-Monterey, CA		
Salt Lake City-Ogden, UT	Wasatch Front Regional Council	
San Antonio, TX	Alamo Area Council of Governments	
San Diego, CA	San Diego Association of Governments	
San Francisco, CA	Association of Bay Area Governments	
San Jose, CA	Association of Bay Area Governments	
Santa Barbara-San Maria-Lompac, CA	Santa Barbara County Association of Governments	
Santa Cruz, CA	Association of Monterey Bay Area Governments	
Santa Rosa-Petaluma, CA	Association of Bay Area Governments	
Savannah, GA		Chatham County-Savannah Metropolitan Planning Commission
Scranton-Wilkes-Barre-Hazleton, PA		
Seattle-Everett, WA	Puget Sound Regional Council	
Shreveport, LA	Northwest Louisiana Council of Governments	
South Bend, IN		
Spokane, WA		Spokane Regional Transportation Council
Springfield, IL		Springfield-Sangamon City Regional Planning Commission
Springfield, MO		
Stockton, CA		
Syracuse, NY	Central New York Regional Economic Development Council	Syracuse Metropolitan Transportation Council
Tampa-St. Petersburg-Clearwater, FL	Tampa Bay Regional Planning Council	Hillsborough County MPO
Terre Haute, IN	West Central Indiana Economic Development District, Inc	
Toledo, OH/MI		Toledo Metropolitan Area Council of Governments
Trenton, NJ	Delaware Valley Regional Planning Commission	
Tucson, AZ	Pima Association of Governments	
Tulsa, OK	Indian Nations Council of Governments	
Tuscaloosa, AL	West Alabama Regional Commission	
Tyler, TX	East Texas Council of Governments	Tyler MPO
Utica-Rome, NY	Mohawk Valley Regional Economic Development Council	
Vineland-Millville-Bridgetown, NJ		South Jersey Transportation Planning Organization
Visalia-Tulare-Porterville, CA	Tulare County Association of Governments	
Waco, TX	Heart of Texas Council of Governments	Waco MPO
Washington DC, MD/VA/WV	Metropolitan Washington Council of Governments	
Waterloo-Cedar Falls, IA	East Central Iowa Council of Governments	
Wausau, WI	North Central Wisconsin Regional Planning Commission	Wausau MPO

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Metropolitan Area	COGs	MPOs
Wichita, KS		Wichita Area MPO
Wichita Falls, TX	Nortex Regional Planning Commission	Wichita Falls MPO
Williamsport, PA	Central Keystone Council of Governments	Williamsport Area Transportation Study
Wilmington, DE/NJ/MD		Wilmington Area Planning Council
Wilmington, NC	Cape Fear Council of Governments	Wilmington Urban Area MPO
Yakima, WA	Yakima Valley Conference of Governments	
York, PA	Capital Region Council of Governments	York Area MPO
Youngstown-Warren, OH	Eastgate Regional Council of Governments	

Notes on the computation of the variable *Geographic Adherence*

Geographic Adherence is a dummy variable which takes value 1 if the boundaries of the Metropolitan Statistical Area (MSA) coincides or there is just a slight mismatch with those of the Council of Government (COG). In order to assign a value for each of the MSAs under analysis, we firstly compute two measures that relate the geographic extensions of the two territorial entity and then we present the whole set of resulting scenarios. Finally, we identify the scenario representing the situation in which the geographic extension of the Metropolitan Statistical Area is barely the same as that of the corresponding Council of Government.

We named *Ratio* the first measure of geographic adherence as it indicates the ratio between the number of people under a COG jurisdiction with respect to the population of the corresponding MSA, i.e.:

$$Ratio \ = \ \frac{Population\ COG}{Population\ MSA}$$

Thereafter, *Coverage* measures the share of population living in the MSA that is represented in the corresponding Council of Government, i.e.:

$$Coverage \ = \ \frac{Population\ MSA\ \cap\ Population\ COG}{Population\ MSA}$$

By combining the values obtained from the two measures, it is possible to identify three general scenarios: a) the MSA is entirely contained in the COG; therefore, $Ratio > 1$ and $Coverage = 1$; b) the COG is entirely contained in the MSA, i.e. $Ratio < 1$ and $Coverage < 1$; c) the COG and the MSA overlaps but both of them have only a fraction that intersects the other. In the latter case, $Ratio$ may be whatever while $Coverage < 1$.

Hence, we hypothesis that the most effective scenario is the one characterised by $Coverage = 1$ and $1.0 \leq Ratio \leq 1.2$, meaning that all the people living in the MSA are represented by the correspondent COG, which geographical extension is identical to that of the MSA or just a little bit greater, in such a way to control for further extension of the autonomous local economic system.

Notes on the First Stage

Data:
The source of CENSUS data is the Integrated Public Use Microdata Series (IPUMS). Samples used are 1% samples for the years 1980 1990 2000. The analysis has been restricted to workers aged between 25 and 65 years old and excludes "self-employed" workers (using the variable CLASSWRK).

Dependent variable:
Hourly wage = *Labour income* / (*Weeks Worked* * *Hours usually worked per week*)
Labour income is the variable INCWAGE, which reports each respondent's total pre-tax wage and salary income - that is, money received as an employee - for the previous year. Sources of income in INCWAGE include wages, salaries, commissions, cash bonuses, tips, and other money income received from an employer. Payments-in-kind or reimbursements for business expenses are not included. Amounts are expressed in contemporary dollars; therefore, they have been adjusted for inflation by using CPI99 that provides the CPI-U multiplier available from the Bureau of labour Statistics to convert dollar figures to constant 1999 dollars.
Weeks Worked is the variable WKSWORK1 for years 1980 and 1990 and variable WKSWORK2 for years 2000. The variables report the number of weeks that the respondent worked during the previous calendar year.
Hours usually worked per week is the variable UHRSWORK which reports the number of hours per week that the respondent usually worked, if the person worked during the previous year. Hourly wage statistics are constructed only for those workers who usually work more than 30 hours per week and more than 30 weeks a year, and whose hourly wage is higher than half of the minimum wage in the corresponding year (1.55 in 1980, 1.90 in 1990, 2.575 in 2000).

Independent variables:
Age, which is the variable AGE that reports the person's age in years as of the last birthday.
Educational Dummies that are constructed by using variable EDUC, indicating respondent's educational attainment, as measured by the highest year of school or degree completed. Four categories are defined: a) Less than high school, b) High school c) 1 to 3 years of college d) 4 years of college or higher.

Gender Dummy that is constructed by using the variable SEX: Gender = 0 if Female.
Ethnicity Dummy that uses RACE: Ethnicity = 0 if Not White.
Occupational Dummies which derive from the census variable OCC. The occupational classification system gets redefined for every decennial Census, especially in 2000. In order to track detailed occupations over time, I followed Autor and Dorn (2013) who provide crosswalk necessary to match occupation codes for different Census year. The authors develop a new occupation system covering the years 1980, 1990, 2000, 2005. Six categories are defined: 1) Managerial and Professional Specialty Occupations, 2) Technical, Sales and Administrative Support Occupations, 3) Service Occupations, 4) Precision Production, Craft and Repair Occupations, 5) Machine Operators, Assemblers and Inspectors and 6) Transportation, Construction, Mechanics (Mining and Agricultural Occupations).
Industrial Dummies which it are obtained from IND1990 which classifies industries from all years since 1950 into the 1990 Census Bureau industrial classification scheme. IND1990 offers researchers a consistent long-term classification of industries. Twelve categories are defined: 1) Agriculture, Forestry and Fishing, 2) Mining, 3) Construction, 4) Manufacturing, 5) Transportation, Communications, and other Public Utilities, 6) Wholesale Trade, 7) Retail Trade, 8) Finance, Insurance, and Real Estate, 9) Business and Repair Services, 10) Personal Services, 11) Entertainment and Recreation Services and 12) Professional and Related Services.
Time Dummies: for the years 1980 1990 2000
Metro Area Dummies: MIGMET5 identifies the metropolitan area in which the respondent used to work five years earlier, if the respondent's workplace was in an identifiable metropolitan area, given confidentiality restrictions (182 metro areas).

Estimation Results Table A6 presents the First Stage estimates for the set of workers observable characteristics (age, ethnicity, gender, education, occupation), industry fixed effect as well as Metropolitan Area fixed effects interacted with time dummies.

Table A6: First Stage Specifications Results - Details

	(I)	(II)	(III)	(IV)
Age	0.0614^{***}	0.0564^{***}	0.0561^{***}	0.0536^{***}
	(85.47)	(84.27)	(84.08)	(81.57)
Age^2	-0.0006^{***}	-0.0006^{***}	-0.0006^{***}	-0.0005^{***}
	(-74.63)	(-69.71)	(-69.48)	(-67.22)
Ethnicity	0.232^{***}	0.159^{***}	0.158^{***}	0.156^{***}
	(119.78)	(88.46)	(87.47)	(87.66)
Gender	0.242^{***}	0.246^{***}	0.239^{***}	0.221^{***}
	(160.16)	(176.81)	(170.43)	(148.82)
Very High Education		0.672^{***}	0.674^{***}	0.664^{***}
		(242.70)	(238.20)	(231.14)
High Education		0.382^{***}	0.386^{***}	0.373^{***}
		(140.65)	(141.05)	(136.97)
Medium Education		0.227^{***}	0.232^{***}	0.220^{***}
		(85.10)	(86.76)	(83.22)
Manager/Professional			0.0884^{***}	0.0993^{***}
			(32.85)	(37.23)
Production			0.202^{***}	0.163^{***}
			(25.19)	(20.33)
Transportation/Construction			0.173^{***}	0.148^{***}
			(32.17)	(27.82)
Machine Operators			0.129^{***}	0.0631^{***}
			(19.72)	(9.61)
Clerical			-0.0153^{***}	-0.00389
			(-4.25)	(-1.10)
Agriculture				-0.249^{***}
				(-33.30)
Mining				0.244^{***}
				(23.16)
Construction				0.101^{***}
				(27.82)
Manufacturing				0.130^{***}
				(49.45)
Transportation				0.166^{***}
				(54.08)
Wholesale Trade				0.0804^{***}
				(21.19)
Retail Trade				-0.120^{***}
				(-40.97)
Finance				0.130^{***}
				(39.48)
Business				0.0310^{***}
				(8.28)
Entertainment				-0.0508^{***}
				(-7.18)
Professional				0.0132^{***}
				(5.16)
N	540740	540740	540740	540740
R^2	0.9626	0.9682	0.9684	0.9693
MSA X Year Dummies	Yes	Yes	Yes	Yes

MSA clustered t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Reference categories for OCCUPATION: Occupation=Service Occupations; for EDUCATION: Education=Low; for GENDER: Gender=Female; for ETHNICITY: Ethnicity=Not White; for INDUSTRY: Industry=Personal Services.

Sensitivity of the results to different approaches to define MSAs

Table A7: Sensitivity Results

	(Initial)	**(Final)**
Density	0.080***	0.075***
	(0.006)	(0.006)
Land	0.084***	0.085***
	(0.007)	(0.007)
City Land	-0.023***	-0.021**
	(0.006)	(0.006)
Market Potential	0.034***	0.038***
	(0.004)	(0.004)
Fragmentation	-0.026***	-0.024***
	(0.005)	(0.004)
Dominance	0.122***	0.126***
	(0.026)	(0.026)
Distance Decay	1.76***	1.69***
	(0.200)	(0.182)
Observations	546	546
Year FE	Yes	Yes
Metropolitan Areas	182	182
Over Identification	0.599	0.360
(p)Over Identification	0.439	0.548
Weak Identification	514.51	401.73
Under Identification	118.72	103.58
(p)Under Identification	0.000	0.000
Endogeneity	8.69	7.56
(p)Endogeneity	0.00	0.00

OLS estimates with Standard Errors clustered by metropolitan area in parenthesis.$*\rho < 0.10,\ **\rho < 0.05, ***\rho < 0.01$.

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