Location-Specific Adjustments in Population and Employment across Metropolitan America

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Abstract: This paper examines the joint adjustment of population and employment numbers across America's metropolitan areas during the period 1990–2015. Current levels of both are estimated, for 10 year periods, using their lagged (own and cross) levels and eight other lagged variables. Population is affected by both human and natural amenities and employment by wages, patents, and other attributes of the workforce. This paper questions the conventional interpretation of the adjustment process by using geographically weighted regression (GWR) instead of standard linear (OLS, 2GLS) regression. Here the various estimates are all local, so the long-run equilibrium solutions for the adjustment process vary over space. Convergence no longer indicates a stable universal solution but instead involves a mix of stable and unstable local solutions. Local sustainability becomes an issue when making projections because employment can quickly lead or lag population in some metropolitan labor markets.

Keywords: adjustment; population and employment; regression; stable and unstable local solutions; local sustainability

1. Introduction

Analysts and policymakers remain keenly interested in the structure and evolution of national metropolitan systems. However, in recent decades, urban scientists in the U.S. have been so preoccupied with such matters as governance, innovation, and inequality that few new insights have been reached regarding *systemic* growth and change across the nation's hundreds of metropolitan areas. In part because of their interests in, and concerns about, spatial equity and regional cohesion, the Europeans now seem to have a superior appreciation of how place-based metropolitan development occurs [1].

During the 1970s geographers like Borchert [2] pointed out that U.S. economic growth was directed by key metropolitan control centers; Pred [3] outlined how an intercity hierarchy emerged to channel this growth; and, using earlier studies, Berry and Horton [4] summarized how these features, interacting with one another, influenced the size-distribution of cities, their industrial specialisms, and the socioeconomic properties of the American metropolitan system. But, aside from a few exceptions, the contributions of geographers to understanding systemic metropolitan growth diminished afterward and were soon replaced by the new insights of economists during the 1980s and 1990s [5]. To some degree this new thinking was built on the ideas of visionaries like Jane Jacobs and regional scientists like Edgar Hoover, Walter Isard, and Martin Beckmann. By the late 1990s a new generation of economists had made great strides in revealing the importance of factors like agglomeration, spatial externalities, and the role of human capital in facilitating the growth of large U.S. urban centers [6,7]. But interest in the systemic aspects of this growth became appreciably narrower in scope just as the models used to understand metropolitan employment and population growth became more sophisticated.

Perhaps the most insightful literature of recent decades has focused on the changing relationship between demographic composition and spatial behavior as household

members move through their life courses. Along these lines, Whisler et al. [8] used the data of Census 2000 to show that highly educated American households, depending on their ages and other attributes, preferred the locations, sizes, and economic specialisms of some cities over those offered by others; using similar longitudinal data sets, contributors from elsewhere extended those findings to other nations and cultures at different geographic scales [9]. For some decades, too, urban scientists have argued that large and diverse superstar cities have acted as high-density escalators (and even elevators) of human opportunity where risk-taking households could enter at a lower level of affluence and expect to depart later at an appreciably higher level [10,11]. This escalator effect has been much easier to distinguish in simpler national metropolitan systems, such as that in the U.K., but is still highly relevant to the U.S. experience. Recently, however, a declining proportion of American households has been able to participate in this process, which once largely ensured better life chances for the so-called middle class because affluence could accumulate in place through widespread home ownership and rising house prices. But in the U.S., and elsewhere, many middle-class jobs have simply been lost or replaced by communications technology, while the remaining opportunities have become distributed across ever-larger numbers of over-qualified workers. Consequently, a few urbanists, including Kotkin [12], soon became disillusioned with various aspects of the widely accepted high-density opportunity model. In fact, recent events unfolding during the Covid-19 pandemic suggest that the current geographic dispersal of workers might become the generational norm as many young households prefer (or require) larger living spaces and choose not to undertake the congested journey-to-work seen in earlier times.

Despite all this research there still exists a tendency among urban scientists to view the effects of the Knowledge Economy on U.S. metropolitan areas in simplistic binary terms. Large urban regions are often said to be sorting into camps of haves and have-nots by economists; widespread areas are classified as being coastal versus flyover, or perhaps sunbelt versus rustbelt, according to various policy-oriented blogs and popular journals; and the changing relationship between population and employment is often categorized as being either supply-driven or demand-driven growth [13–15]. In truth the recent evolution of the U.S. metropolitan space-economy has been much more nuanced and, at both the local and regional levels, more uneven than these binary designations suggest [16].

In the spirit of existing spatial-econometric papers by the authors, this study focuses on the mutual adjustment that has recently taken place between population and employment numbers across metropolitan America [17,18]. Using 10-year temporal lags, both aspects of this mutual adjustment are examined every five years between 1990 and 2015 (the last dependable year for some of the data). A spatial model, which can be estimated by linear regression, assumes that current population and employment numbers must jointly adapt to their (own and cross) prior numbers, where this adaptation depends upon various place-specific conditions [19]. These exogenous conditions include prior natural and human-created amenities, which largely influence population change, and a handful of other factors—including prior wages and age of the workforce—that largely influence employment change.

Past studies have identified *global* estimates for metropolitan regions, where a series of 2 by 2 "growth operator" matrices trace out the ever-evolving relationship between current population and employment levels and their earlier levels [20]. The coefficients of these matrices usually stabilize over time, so a single universal endogeneity matrix is thought to be appropriate for all the metropolitan places in the study. Alternatively, this paper generates *local* estimates instead of these global estimates, in effect estimating a separate endogeneity matrix for each metropolitan place. As expected, the pattern of coefficients in these growth operator matrices varies substantially across the national landscape. Moreover, the local effects of the contextual variables, especially amenities and wages, are also shown to vary a lot across those metropolitan areas.

These local estimates are generated by adopting geographically weighted regression (GWR), although other methods exist for revealing the local interactions between popula-

tion and employment [21]. As a result, there is no longer a unique equilibrium solution but, instead, a distribution of location-specific equilibrium solutions. Moreover, in those situations where population or employment numbers grow too quickly, or too slowly, long-run equilibrium solutions might not even exist. In fact, it is now possible for broad regions of the nation to exhibit stable adjustment solutions but small regions or pockets to exhibit unstable solutions. This paper shows how the stability existing between people and jobs changed for those 377 metropolitan areas that were located across the lower 48 U.S. states between 1990 and 2015.

Like earlier studies, the four coefficients of the endogeneity matrix are used to determine how the initial or "short-run" balance between people and jobs should change in the future [17,18]. As already noted, the column elements of the endogeneity matrix reveal the total (direct and indirect) effects of earlier conditions on the more recent levels of population and employment in each metropolitan area. Repeated matrix multiplication is then used to shift, sometimes incrementally, the relative composition of each column effect one period at a time; as matters turn out, the projected "long-run" relationships, generated by numerous rounds of such multiplication, can prove to be very different from the initial or short-run relationships.

Various urban analysts have claimed that these metropolitan economies are leading the U.S. through a new creative age—one that is fraught with many social tensions and economic disruptions. Although a binary classification is much too general, the nation's urban-based regional economies are certainly sorting into those with more advanced human capital and those with less advanced human capital [13,22,23]. More and more, too, it appears that the economic health of the nation's rural and micropolitan economies will be dictated by their location relative to the larger and more dynamic metropolitan economies [24]. Current research suggests that many metropolitan areas currently straddle a technological fence where they could land on either side [13,25]. However, urban policy-makers are still divided over whether government support for the so-called backward or lagging regions should be more person-based or place-based. This paper sheds new light on this very important spatial-welfare issue by projecting population and employment numbers that are no longer spatially uniform across the national metropolitan landscape. A series of place-specific projections, all using 10-year lags, suggest that a lot of variation in economic health will continue across the nation's metropolitan landscape during the upcoming decades. The estimates of this paper reveal how certain policy-related variables, including amenities and wages, can redirect the overall adjustment that occurs between the population and employment numbers of these metropolitan places.

2. Bidirectional Population and Employment Change

The 1970 Census revealed that, somewhat surprisingly, many of America's non-metropolitan counties were growing at the expense of their metropolitan counterparts. This remarkable turnaround process, first noted by people like Beale [26], soon attracted the interest of many regional and urban scientists. For the most part economists viewed this as evidence of job restructuring but others, including demographers, saw this as evidence of deconcentrating households [14,15,27,28]. But, taking a more comprehensive stance, Muth [29] argued that the U.S. space-economy was just exhibiting uncertainty in the direction of causality between changes in population (involving the choices of households) and changes in employment (involving the choices of businesses). Thus, the turnaround topic became yet another chicken and egg problem—one where the twin distributions of population and employment would have to be endogenously analyzed [30]. This bidirectional hypothesis is now increasingly, but not entirely, accepted in the regional and urban sciences.

Before analysts in the U.S. witnessed this national counter-urbanization of the 1960s, many believed that regional employment change necessarily preceded regional population change, or that people always followed jobs [31]. But some quickly became convinced that swelling population numbers could instead drive regional employment change, where jobs

followed people as an alternative scenario [32]. As mentioned above, this led to the binary categorization of demand-induced growth versus supply-induced growth [14,15]. In truth, these opposing tendencies are both continuous and highly correlated, attributes that make it difficult to discern which is the more important in transforming the social and economic fabric of the post-industrial space-economy [17,18].

As Isserman [32] anticipated, the models devised to analyze this bidirectional change have come from a variety of disciplines and perspectives. Analysts like Greenwood [33] and Graves [34,35] observed that U.S. households often behaved differently from expectations and frequently shifted their residences from places of high economic opportunity to places of low economic opportunity. This finding brought key demographic concepts, like the life course, to the forefront for consideration and empirical testing. Here the thoughtful paper by Sjaastad [36] proved especially influential because he suggested that households will often see short-distance mobility or long-distance migration as an investment decision. Moreover, the path-breaking work done on hedonic markets by people like Rosen [37] and Roback [38] clarified other matters and provided a rationale for why many households might migrate over long distances. In short, households might be content to trade off the higher wages and salaries that can be earned at one place for the more valuable natural or human-created amenities found at another place. Moreover, considerable research stresses that households exhibit significant heterogeneity—in size, composition, wealth, and risk aversion—and this factor alone might drive or constrain their migration decisions; consequently, in any case, households with very different attributes might make remarkably different choices about where to live and work [39]. Finally, various studies of metropolitan labor markets argue that some forward-looking firms will always anticipate the shifting preferences of their workers and consider locating, or perhaps even relocating, their businesses to areas that are believed to be richer in non-traded amenities [40]. Given the remarkable sizes of the nation's very largest metropolitan areas this relocation might happen either inside or outside the area's existing boundaries (or commuting zones).

It is now widely accepted, at least in the U.S., that amenity-based externalities, of various types, will have a pervasive effect on the movements of households over fairly long periods of time while economic opportunities, which are more restricted in space by trading and commuting costs, will influence the movements of households in diverse ways, depending in part upon the timing of events [41]. In any case, numerous studies have lent strong support to Muth's bidirectional claims and, increasingly, population and employment shifts are not analyzed as if they represented entirely independent trends. In fact, population studies that do not appreciate this endogeneity are apt to under- or overpredict the effects of other demographic factors, including the age or composition of the household, on the movement of people between regions. So, the notion of the *spatial equilibrium* has been adopted to accommodate these simultaneous changes, which in turn reflect the myriad decisions made by both workers and firms. In any case, the joint adjustment perspective has become popular not only for explaining short-term trends in population and employment numbers, but also for studying the long-term movements of demographic and economic agents that occur both within and between metropolitan regions [41,42].

3. The Adjustment Process

Partial adjustment models have been widely used throughout economics, especially in the analysis of money markets and the demand for certain consumer goods, and regional adjustment models are simply the spatial versions of these. Of course, distinctive problems do arise once the adjustment process is embedded in space as well as time. Interestingly, these spatial models first appeared in the research of regional science addressing the distribution of people and jobs within regions and not between separate regions [43,44]. Regional adjustment models only became popular in the U.S. after the studies of Carlino and Mills [19] and Clark and Murphy [45], who each introduced numerous exogenous variables to control the mutual adjustment of population and employment numbers across

thousands of contiguous U.S. counties. Seen together, these two studies provided interesting insights into some regional features that were just emerging in the U.S. post-industrial space-economy during the 1970s and 1980s. Among other matters, the results indicated that public choices, in the form of unionization rates or taxation levels, might affect the equilibrium properties of the overall adjustment process. Later studies of regional adjustment models have clarified some key specification issues, introduced various diagnostics, and have even addressed the thorny problem of scale [46,47].

3.1. Global Estimates

In the (simplest) 2 by 2 adjustment model the two bodies of population and employment are seen to be inexorably moving toward their equilibrium states. But these final states might never actually be reached. Instead, the two equilibria act more like targets that also evolve over time—due to macroeconomic shocks, demographic reversals, or technological disruptions—because the parameters that control the ongoing adjustment process can also shift. In any case, estimation is carried out on both aspects of the adjustment process or, preferably, on the reduced forms of those twin aspects. Once expressed in the more transparent reduced forms, as seen below, current estimates are based on *own* (lagged) levels of both endogenous variables, *cross* (lagged) levels of those endogenous variables, and several *own* (lagged) exogenous variables. So, to be clear, during some specified time interval, population adjusts to some earlier state of employment but, at the same time, employment adjusts to some earlier state of population. To operationalize matters, however, current population $POPUL_t$ is taken to adjust to an *estimate* for current employment $EMPLY^*_t$ and, similarly, current employment $EMPLY_t$ is taken to adjust to an *estimate* for current population $POPUL^*_t$. Since Carlino and Mills [19] analysts tend to make use of Census data, so the adjustment period is usually assumed to be a decade in length, but the most appropriate time lag is not really known. It remains unclear how important this time restriction is.

For the most part the two equations tracing out the adjustment process are estimated by adopting two-stage least squares (2GLS) regression procedures. Here the 2nd-stage results are:

$$POPUL_t = a_1 + b_1 POPUL_{t-1} + c_1 EMPLY^*_t + \mathbf{d_1 VECTR_{t-1}} + e_1 \qquad (1)$$

$$EMPLY_t = a_2 + b_2 POPUL^*_t + c_2 EMPLY_{t-1} + \mathbf{d_2 VECTR_{t-1}} + e_2 \qquad (2)$$

The coefficient c_1 indicates the rate at which population numbers are adjusting to employment while the coefficient c_2 indicates the rate at which employment numbers are adjusting to population. The underlying supposition is that the incremental changes in both current population and employment will diminish over time, and a spatial equilibrium will be reached. The magnitudes of these two coefficients indicate the differential speeds of the two aspects of the overall joint adjustment. The estimates in reduced form for these two adjustment equations can be reached through substitution [17,18]. When making the various estimates for current employment and population, a series of exogenous (initial or prior) variables are typically placed in a contextual vector $\mathbf{VECTR_{t-1}}$. This vector is required because the twin distributions of errors are likely correlated so the estimates of those variables will be biased. The two reduced-form expressions are expressed as follows:

$$POPUL_t = g_1 + h_1 POPUL_{t-1} + i_1 EMPLY_{t-1} + \mathbf{j_1 VECTR_{t-1}} + k_1 \qquad (3)$$

$$EMPLY_t = g_2 + h_2 POPUL_{t-1} + i_2 EMPLY_{t-1} + \mathbf{j_2 VECTR_{t-1}} + k_2 \qquad (4)$$

which can, of course, be alternatively estimated directly by OLS regression (or a similar technique). In this paper all variables have been transformed using logarithms, so the various coefficients are in fact *elasticity* estimates. Several sources, including [18], show how numerical reduced-form estimates can be calculated on a step-by-step basis.

Finally, the estimation itself can be carried out for the entire time interval or for shorter, but contiguous, intervals that comprise the entire period. Quite often, too, some overlapping of these shorter intervals is involved. This pooling of data serves to "average out" the estimates and offers more observations for study, but often obscures any shifts in the estimates of population and employment that might reflect either a systemic shock or represent a system-wide secular or cyclical tendency in the population and employment numbers.

To address shifts instead of levels some analysts prefer to modify the left-hand side of Equations (1) through (4) prior to estimation. But this operation is simply cosmetic, and only reduces the magnitude of the adjusted coefficient of determination in each instance. In the arithmetic case, the new estimates for h_1 and h_2 become h_1-1 and h_2-1, respectively, in Equations (3) and (4), while all the other estimates exactly remain the same. Alternatively, in the logarithmic case, the modified equations—that now address *growth* instead of *change*—are once again h_1-1 and h_2-1, respectively. When three or more endogenous variables are estimated the issue of convergence can become somewhat problematic once the extra coefficients appear in the growth operator matrix. In any case, these new endogenous variables are typically chosen from those already included in the vector of exogenous variables.

As already stated, the joint adjustment process might never reach a long-run equilibrium if one of the endogenous variables grows too quickly or too slowly. For example, rapid household growth confined only to some metropolitan areas (in the Sunbelt) might mean that population numbers outstrip the corresponding employment numbers at these locations, and the features of the adjustment process must adapt step-by-step to these new circumstances. Or, alternatively, jobs might quickly swell only at some places (in the oil patch) and employment might outstrip population numbers at those locations. So, it is imperative that a test for convergence be applied to the reduced-form equations (see below). As discussed in detail elsewhere [17,18], such convergence means that the standardized array of elements down each column of the long-run equilibrium matrix **M*** becomes increasingly similar. Moreover, their ratios (or shares) become identical to those uncovered in the so-called unit vector [48]. While the future values projected for the two endogenous variables are fixed throughout each projection period by the so-called "growth operator" matrix, these values are constantly updated by the subsequent rounds of matrix multiplication. Here the use of the projection matrix is much the same as that for the Markov models of population redistribution that are well known elsewhere [20,49,50].

3.2. Local Estimates

The methodology outlined above generates global estimates for the lagged endogenous variables and the other lagged contextual conditions. But there are conceptual problems with this approach even when accommodation is made for spatial dependency. The most severe problem is that the effect of each contextual variable—including the impact of human amenities on population and the impact of wages on employment—is assumed to be invariant across the landscape. Clearly, an alternative, and superior, methodology is needed that generates local estimates of these endogenous and exogenous effects.

This paper adopts geographically weighted regression (GWR) to accomplish the task of making these location-specific estimates [21,51]. Other similar methods exist, including the spatial expansion approach, but GWR seems the best for addressing problems where the (spatial) density of observations is so varied. Put simply, this method adapts the kernel configuration for sampling to this uneven density to ensure that all local estimates are made using the same number of surrounding neighbors. The logic behind GWR estimation, nicely reflecting Tobler's first law of geography, is very straightforward: the influence of nearby observations is given much greater weight than the influence of more distant observations. Although different versions of GWR now exist, the results of this paper are based on the original version of the model where all variables, endogenous and exogenous alike, are given local estimates. As before, each of these estimates can be interpreted as an (elasticity) effect that is specific to the vicinity of the metropolitan area.

The adjustment process is modeled exactly as before but now the estimates are made separately for each of 377 metropolitan economies. Again, the various estimates are made at four different points in time, thereby providing a series of 10-year snapshots of the nation's changing demographic and economic conditions between 1990 and 2015. Denoting each of these time intervals by the subscript *s* where *s* = 1,2,3,4, the two reduced-form expressions are now:

$$POPUL_{st} = g_{zs1} + h_{zs1}POPUL_{st-1} + i_{zs1}EMPLY_{st-1} + \mathbf{j_{zs1}VECTR_{st-1}} + k_{zs1} \tag{5}$$

$$EMPLY_{st} = g_{zs2} + h_{zs2}POPUL_{st-1} + i_{zs2}EMPLY_{st-1} + \mathbf{j_{zs2}VECTR_{st-1}} + k_{zs2} \tag{6}$$

and the additional subscript *z* on the coefficients is only a reminder that nearby observations are weighted more than distant observations in the estimation of local values for population $POPUL_{st}$ and employment $EMPLY_{st}$. As for stability, the discussion above, which pertained to global estimates made across all metropolitan areas, remains appropriate for the various place-specific estimates that are made by applying geographically weighted regression.

4. Data, Variables, and Conjectures

As in other recent studies, the analysis focuses on 377 of the 381 metropolitan statistical areas that are monitored by the Bureau of Economic Analysis [16,52,53]. Four cities in Alaska and Hawaii were not considered because they were extreme spatial outliers, a property that violates the geographic nearness needed for GWR or for assessments of spatial dependency in OLS. The BEA website [52] discloses that, between 1990 and 2015, the mean population *POPUL* of these areas rose approximately 29.6% to 319K while, at the same time, their mean employment *EMPLY* rose approximately 37.8% to 182K. While dozens of the smallest places had not yet achieved metropolitan status for Census 1990, a good number of these had achieved micropolitan status (a new and intermediate category) for Census 2000.

A large literature suggests that current population should be affected by the quality and quantity of natural amenities [17,19,54]. Here natural amenities were captured by data addressing both cooling degree-days *CDGDY*, which ranged from 109 (Seattle, WA, USA) to 3984 (Miami, FL, USA), and heating degree-days *HDGDY*, which ranged from 245 (Miami, FL, USA) to 9897 (Duluth, MN, USA). In general, cooling degree-days were lowest along the Pacific Coast and heating degree-days were lowest in the desert Southwest and throughout the humid Southeast. But both figures varied considerably by temperature, humidity, and moisture across the large land mass of the continental U.S. [55,56]. These data were assumed to be constant over the 25-year study period and accommodation was not made for any local or regional variation in utility rates, even though electricity is widely needed to operate air conditioning. Other indices for natural amenities were available for adoption but the degree-day indices are both continuous and objective, even if they largely reflect only the climate differences across the metropolitan locations [5].

Current population was also conjectured to be affected by the quality, quantity, and availability of human-created amenities [22,57]. These amenities *HAMEN* were estimated for each 10-year interval by first regressing median house values on per capita income, heating degree-days, and cooling degree-days, and then selecting the residuals as net measures of those house values [54]. Some experimentation disclosed that these regressions lost a fair bit of their explanatory power once total degree-days were used instead of its two components. Other evidence exists that these residuals, after being transformed into positive numbers, appear to be a good indirect index of human amenities. In general, certain large cities, including New York, NY and Washington, DC, perform well because of their museums, galleries, and fine restaurants. Likewise, numerous smaller college and university cities, including Ames, IA and Boulder, CO, rank highly because they have valued public goods (including health-care facilities) and they are characterized by a vibrant local ambience. Based on current dollars [52], between 1990 and 2015, the metropolitan median house value rose on average some 24.1% to $170K; at the same time,

personal income rose on average some 145.4% to $42.7K. Given present purposes, the three conjectures of greatest interest were as follows: population numbers were driven lower by *CDGDY* (-) and *HDGDY* (-) but higher by *HAMEN* (+). In the first two instances it is assumed that households generally prefer mild to extreme climates and often seek out those locations offering low scores for either cooling or heating degree-days. In the third instance it is assumed that households generally prefer more as opposed to less public goods and local ambience, even if those human amenities become capitalized into higher house values [54].

Current employment was also conjectured to be significantly affected by average wages and salaries, industrial specialization, and patenting activity [17,19]. Expressed in current dollars [52], between 1990 and 2015, average annual wages and salaries *WAGES* rose approximately 115.4% to $44.6K. Although all types of manufacturing jobs were considered in the earlier study by Mulligan and Nilsson [18], only industrial specialization *PPROF* was considered here; this was measured by the incidence of human-capital employment arising in the professional, scientific, and technical services (classified as NAICS 54). Between 1990 and 2015 the average importance of these knowledge-intensive jobs rose from 4.27% to 5.18% when expressed as a proportion of all metropolitan jobs [40]. Patenting *PATEN* was included only because this activity is often chosen to differentiate between highly creative cities and less creative ones [13,18,22]. Although there is only weak evidence for this relationship, the thinking was that creative cities would eventually attract more new businesses than non-creative cities. In any case, between 1990 and 2015 the average patent density (patents per 1,000 persons) in the 377 metropolitan economies nearly doubled in size from 0.161 to 0.318 [58,59]. Here the first conjecture (*WAGES*, -) recognizes that firms generally prefer to pay lower wages to their workers, although this tendency varies a lot both with the industry concerned and with the skills (or occupations) already acquired by those workers. The second conjecture (*PPROF*, +) indicates that, due to spatial spillover and local learning effects, overall employment levels in the post-industrial economy should increase more in those places where technical and scientific expertise is initially high. The third conjecture *(PATEN*, +), the weakest of these three, recognizes that highly innovative metropolitan economies should generate more overall jobs through spread and spin-off effects than less innovative economies.

This study also addresses two other conditions that have not been included in most of these other studies [48]. One of these is proprietary employment, which is a popular measure of the incidence of entrepreneurship in regional economies [60,61]. Of course, self-employment can be measured in different ways but, for present purposes, the figures released in the BEA's Economic Profiles have been adopted [52]. Between 1990 and 2015, the importance of self-employment *PROPR* jobs rose on average from 15.7% to 20.5% when expressed as a proportion of all metropolitan jobs. In the U.S. space-economy, self-employment tends to be higher throughout the Sunbelt states where older people often start up small businesses or they decide to work part-time, and where state-level right-to-work laws are generally weaker. Finally, to control for the differential age composition of the various metropolitan labor markets, a prime workforce variable *PWFOR* was calculated. But this variable did not exactly address the ages of employees and, instead, dealt with the ages of people: it was calculated as the ratio between those persons in the 18–44 age cohorts and those persons in all age cohorts. People in this intermediate age group are widely believed to be more productive, on average, than those in either younger or older age groups. The average of this prime workforce proportion fell from 31.4% in 1990 to 25.0% in 2015 as the population aged in most metropolitan areas. Across the entire 25-year study period, higher initial rates of self-employment (*PROPR*, +) and higher initial prime workforce ratios (*PWFOR*, +) were both conjectured to have a positive effect on overall job numbers in the nation's diverse metropolitan economies.

5. Results

5.1. Regression Estimates

The first set of results compares the reduced-form estimates for ordinary least-squares (OLS) and least-squares adjusted for spatial dependency (2GLS) to the average estimates (across 377 observations) generated by geographically weighted regression (GWR). The 2GLS estimates, which account for spatial lags, use the approach outlined by Kelejian and Prucha [62] with a 400-km threshold. The most interesting results, shown in Tables 1 and 2, are the elasticity estimates, respectively, for population and employment numbers covering the four decadal periods prior to the years 2000, 2005, 2010, and 2015, respectively. To save space, only the conjectured estimates of interest are shown: the two endogenous variables along with three contextual variables for population and the two endogenous variables along with five contextual variables for employment. In general, GWR deflates the own-effect of lagged population and inflates the cross-effect of lagged employment on current population; also, GWR deflates the cross-effect of lagged population and inflates the own-effect of lagged employment on current employment. In fact, across the 1508 (377×4) observations pooled over the four time periods, the elasticity estimate on $POPUL_{t-1}$ falls from 0.944 (GS2SLS) to 0.913 (GWR) and the estimate on $EMPLY_{t-1}$ climbs from 0.055 to 0.086 in the population equation; at the same time, the estimate on $POPUL_{t-1}$ falls from 0.057 (GS2SLS) to 0.029 (GWR) and the elasticity estimate on $EMPLY_{t-1}$ climbs from 0.943 to 0.969 in the employment equation. Clearly, the four coefficients of the 2 by 2 endogeneity matrix are shifted away from an overall population effect toward an overall employment effect when using geographically weighted regression. As for the contextual effects only three differences are worthy of note. Again, looking across all 1508 observations, GWR generates a much greater effect (0.104 versus 0.066) for human amenities in the population equation, and much smaller effects for both self-employment (0.124 versus 0.170) and wages (−0.196 versus −0.238) in the employment equation. The estimates in Table 1 suggest that the gap in the human amenities effect narrowed in the middle years but the estimates in Table 2 suggest that the gap in the self-employment effect widened over time, while the gap in the wage effect narrowed over full study period. Other shifts are evident in specific time periods, including a rise in the importance of a prime workforce in the period 1995–2005 and a fall later in the period 2005–2015, but these are the three most pervasive shifts (Table 2).

Table 1. Reduced-Form Population Estimates: 10 Year Lags.

	OLS	2GLS	GWR	OLS	2GLS	GWR
		90-00			95-05	
Constant	2.609 *	2.276 *	1.569	1.167 *	1.024 *	0.328
POPUL	0.894 *	0.888 *	0.872	0.945 *	0.950 *	0.903
EMPLY	0.109 *	0.111 *	0.132	0.050	0.044	0.090
HAMEN	0.083 *	0.093 *	0.114	0.142 *	0.143 *	0.117
CDGDY	−0.009	−0.006	−0.018	0.005	0.006	−0.013
HDGDY	−0.067 *	−0.060 *	−0.062	−0.057 *	−0.054 *	−0.056
		00−10			05−15	
Constant	1.285 *	1.092 *	0.369	0.489	0.320	0.769
POPUL	0.982 *	0.997 *	0.967	0.965 *	0.974 *	0.911
EMPLY	0.018	0.002	0.033	0.029	0.019	0.087
HAMEN	0.135 *	0.133 *	0.141	−0.010	−0.009	0.044
CDGDY	0.012	0.015 **	0.007	0.031 *	0.033 *	0.034
HDGDY	−0.031 *	−0.026 *	−0.025	−0.005	−0.001	−0.015

Note: n = 377; * 0.01 level; ** 0.05 level. OLS does not address spatial dependence and 2GLS addresses spatial dependence; GWR is the average across all observations.

Table 2. Reduced-Form Employment Estimates: 10 Year Lags.

	OLS1	2GLS	GWR	OLS1	2GLS	GWR
		90-00			95-05	
Constant	2.985 *	2.509 *	0.373	1.914 *	1.600 *	1.115
POPUL	−0.020	−0.028	−0.017	0.039	0.050	0.028
EMPLY	1.023 *	1.027 *	1.120	0.955 *	0.942 *	0.962
WAGES	−0.397 *	−0.296 *	−0.261	−0.142 *	−0.089	−0.099
PWFOR	0.290 *	0.173 *	0.331	0.015	−0.038	0.239
PROFS	0.040 *	0.040 *	0.031	0.066 *	0.062 *	0.059
PATEN	0.015 **	0.017 *	0.013	−0.002	0.000	−0.004
PROPR	0.124 *	0.081 *	0.121	0.117 *	0.092 *	0.144
		00−10			05−15	
Constant	0.040	−0.193	1.004	−0.384	−0.727	1.350
POPUL	0.141 *	0.159 *	0.113	0.061	0.080	−0.009
EMPLY	0.846 *	0.827 *	0.881	0.939 *	0.919 *	1.015
WAGES	−0.229 *	−0.189 *	−0.246	−0.186 *	−0.136 *	−0.179
PWFOR	0.393 *	0.350 *	0.361	0.341 *	0.288 *	0.227
PROFS	0.135 *	0.130 *	0.100	0.115 *	0.110 *	0.091
PATEN	−0.006	−0.004	0.002	0.010	0.012 **	0.012
PROPR	0.211 *	0.187 *	0.135	0.200 *	0.176 *	0.096

Note: n = 377; * 0.01 level; ** 0.05 level. OLS does not address spatial dependence and 2GLS addresses spatial dependence; GWR is the average across all observations.

5.2. Stability

As pointed out by Carlino and Mills [19] the stability of the population and employment estimates should be examined, even though the practicality of any equilibrium might be questioned [63]. Here it has become customary to examine the lagged coefficients of the 2 by 2 growth operator matrix **M** = $(h_1, i_1; h_2, i_2)$, where h represents population and i represents employment. The subscripts signify that two equations are being estimated, and the semi-colon simply delimits the separate rows for these equations [17,18]. When the eigenvalues (or characteristic roots) are real for the endogeneity matrix **M**, convergence (eventually) must take place in the adjustment process and a long-run equilibrium exists. At the global equilibrium, estimated by OLS regression, or at each local equilibrium, estimated by GWR, the array of population coefficients in **M*** is just matched by the array of employment coefficients in that same matrix. The dominant (larger) eigenvalue is selected to indicate the correct solution for stability in the adjustment process [49,50].

In fact, stability in the GWR estimates was almost universal. In the first period, there were only 2 cases of instability; in the second period, 16 cases; and in both the third and fourth period, no cases at all. Clearly the period 1995–2005 exhibited the greatest degree of instability for the four periods that were examined. Five of these places, including Houston, were found in the oil patch district of Texas and three more, including Dubuque, IA and Eau Claire, WI, were strung out along the Mississippi River and its tributaries in Middle America. The remaining places were distributed across the nation and this list included some agricultural economies such as Chico, CA and Yakima, WA; but, in any case, none was a large metropolitan area.

Table 3 provides further evidence of this stability by showing how remarkably low was the degree of volatility in the reduced-form coefficients at four different points in time. The correlation coefficients shown in the various sections of this table relate, in clockwise order, to the degree of association between (i) the estimates of $POPUL_{t-1}$ in the current population equations; (ii) the estimates of $EMPLY_{t-1}$ in the current population equations; (iii) the estimates of $POPUL_{t-1}$ in the current employment equations; and (iv) the estimates of $EMPLY_{t-1}$ in the current employment equations. So, to clarify, r = 0.794 denotes the very strong association between the 377 estimates of $POPUL_{t-1}$ for the period 1990–2000 and the 377 estimates of $POPUL_{t-1}$ fifteen years later for the period 2005–2015. The own-variable correlations, all very high, were to be expected but the strong cross-variable correlations were not; however, these high latter figures appear to be in part due to the way GWR

generates it place-specific estimates. The comparable correlations for the employment equations were also very strong. The only remarkable difference between the two sets of estimates was the drop in both the own- and cross-variable correlation coefficients for employment across the 377 metropolitan areas during the period 2000–2010, when the Great Recession was taking place. The strength of the association between the estimates of 2000 and those of 2010 were 0.868 (own) and 0.850 (cross) for the population equations, but these two figures dropped to 0.621 (cross) and 0.656 (own) for the employment equations. Nevertheless, the stability over time in the various place-specific estimates of population and employment was truly remarkable.

Table 3. Correlations across the GWR Estimates of Current Population and Current Employment.

	2000	2005	2010	2015	2000	2005	2010	2015
	$POPUL_t$							
	$POPUL_{t-1}$	$POPUL_{t-1}$	$POPUL_{t-1}$	$POPUL_{t-1}$	$EMPLY_{t-1}$	$EMPLY_{t-1}$	$EMPLY_{t-1}$	$EMPLY_{t-1}$
2000	1.000	0.920	0.868	0.794	1.000	0.919	0.850	0.810
2005	0.920	1.000	0.961	0.844	0.919	1.000	0.957	0.853
2010	0.868	0.961	1.000	0.915	0.850	0.957	1.000	0.917
2015	0.794	0.844	0.915	1.000	0.810	0.853	0.917	1.000
	$EMPLY_t$							
	$POPUL_{t-1}$	$POPUL_{t-1}$	$POPUL_{t-1}$	$POPUL_{t-1}$	$EMPLY_{t-1}$	$EMPLY_{t-1}$	$EMPLY_{t-1}$	$EMPLY_{t-1}$
2000	1.000	0.926	0.621	0.822	1.000	0.911	0.656	0.867
2005	0.926	1.000	0.727	0.885	0.911	1.000	0.796	0.910
2010	0.621	0.727	1.000	0.856	0.656	0.796	1.000	0.842
2015	0.822	0.885	0.856	1.000	0.867	0.910	0.842	1.000

This issue deserves more discussion focusing on the nation's very largest metropolitan economies. The four reduced-form coefficients of **M** are shown for each of the nation's 15 largest metropolitan areas in Table 4, covering 1990 to 2000, and then in Table 5, covering 2005 to 2015. Even across this small number of metropolitan areas, a certain amount of variation is visible in the signs and the sizes of these key estimates. While stability occurs in all 15 instances, the property of sustainability is not universal (see below). In general, it should be noted that the variation in the estimates of the four estimates declined over time. Nevertheless, the pattern of coefficients for each large economy changed very little over the 25-year study period; for example, the figures for Boston changed marginally from **M** = (0.9074, 0.1054; 0.0405, 0.9773) for 2000 to **M** = (0.9310, 0.0672; 0.0252, 0.9800) for 2015. In fact, a simple 3-cluster classification based solely on these four coefficients is identical in those two separate time periods, where two other economies resemble New York, three others resemble Chicago, and the remaining seven are more like Los Angeles. This is another remarkable result given the shifts noted in the values and signs of the endogenous variables.

To explore matters even more, consider the four GWR estimates for Chicago based on the final 10-year period 2005–2015, where **M** = (0.9418, 0.0568; 0.0432, 0.9648). Stability in the long run occurs for Chicago because the two roots can be shown to be real and the value of the dominant eigenvalue is $\lambda = 1.0041$. This local convergence leads to the specification of a place-specific unit vector, which indicates the relative importance of the two endogenous variables at the long-run equilibrium. Here the ratio between population and employment at this equilibrium is 0.9109 to 1.0000, meaning that the ratio, expressed in logarithms, in the unit vector is (0.4767; 0.5233). Once transformed into arithmetic format, this ratio is (0.4884; 0.5116), and both unit vectors indicate that employment clearly exceeds population at the long-run employment. As noted in the tables, all 15 of these large metropolitan areas

have stable solutions for the two 10-year intervals of time. However, the composition of the unit vectors can be somewhat different in the various places; for instance, the coefficients for Seattle in the last period are $\mathbf{M}$ = (1.0273, −0.0318; 0.0871, 0.9112), where λ = 0.9937, and the unit vector (in logarithmic format) is (0.4866, 0.5134). So, Chicago would be expected to have a slightly higher population-to-employment ratio than Seattle when convergence eventually occurs in both places.

Table 4. Reduced-Form Estimates of Population and Employment: 2000.

Metro	$POPUL_t$ $POPUL_{t-1}$	$POPUL_t$ $EMPLY_{t-1}$	$EMPLY_t$ $POPUL_{t-1}$	$EMPLY_t$ $EMPLY_{t-1}$	Stable	Sustain
New York	1.017	−0.015	0.020	0.970	Yes	Yes
Los Angeles	0.779	0.223	−0.098	1.100	Yes	Yes
Chicago	0.847	0.137	−0.027	1.028	Yes	No
Dallas	0.900	0.093	0.033	0.976	Yes	No
Houston	0.716	0.283	−0.106	1.102	Yes	Yes
Philadelphia	0.899	0.140	0.048	0.984	Yes	Yes
Washington	0.867	0.131	0.009	0.995	Yes	No
Miami	0.810	0.186	−0.053	1.049	Yes	Yes
Atlanta	1.118	−0.108	0.148	0.862	Yes	Yes
Boston	0.907	0.105	0.041	0.977	Yes	Yes
San Francisco	0.851	0.147	−0.063	1.065	Yes	Yes
Phoenix	0.833	0.161	−0.050	1.048	Yes	Yes
Riverside	0.790	0.217	0.127	0.895	Yes	Yes
Detroit	0.801	0.204	−0.138	1.143	Yes	Yes
Seattle	1.032	−0.035	0.063	0.928	Yes	Yes

Note: Solution is sustainable if population estimate exceeds employment estimate in 2020 using 2000 levels as base figures.

Table 5. Reduced-Form Estimates of Population and Employment: 2015.

Metro	$POPUL_t$ $POPUL_{t-1}$	$POPUL_t$ $EMPLY_{t-1}$	$EMPLY_t$ $POPUL_{t-1}$	$EMPLY_t$ $EMPLY_{t-1}$	Stable	Sustain
New York	1.021	−0.025	0.081	0.917	Yes	No
Los Angeles	0.838	0.162	−0.079	1.087	Yes	No
Chicago	0.942	0.056	0.043	0.964	Yes	No
Dallas	0.937	0.062	0.034	0.974	Yes	No
Houston	0.879	0.119	−0.041	1.049	Yes	No
Philadelphia	0.932	0.064	0.018	0.983	Yes	Yes
Washington	1.022	−0.026	0.011	0.999	Yes	No
Miami	0.852	0.148	−0.057	1.067	Yes	No
Atlanta	1.031	−0.034	0.083	0.914	Yes	Yes
Boston	0.931	0.067	0.025	0.980	Yes	No
San Francisco	0.817	0.182	−0.117	1.123	Yes	No
Phoenix	0.823	0.176	−0.107	1.114	Yes	Yes
Riverside	0.830	0.167	−0.097	1.101	Yes	Yes
Detroit	0.824	0.172	−0.102	1.107	Yes	Yes
Seattle	1.027	−0.032	0.087	0.911	Yes	Yes

Note: Solution is sustainable if population estimate exceeds employment estimate in 2035 using 2015 levels as base figures.

5.3. Sustainability

In both examples above population numbers exceed employment numbers when the adjustment rounds begin but, at the final equilibria, employment comes to exceed population in both instances. This, of course, is not a property that can be violated in stand-alone labor markets. However, this property is not a tight constraint in the same sense

for county-based studies where cross-commuting occurs [30]. So, the two labor markets are slowly transformed, at different rates, from sustainable to unsustainable states as the rounds of adjustment unfold. So, the interesting question arises of identifying the exact point in time when this shift to unsustainability occurs? To address this problem, consider the condition $POPUL_t = \sigma EMPLY_t$, where $\sigma > 1$ is a multiplier reflecting the relative size of the non-working or dependent population in the final year of the estimation period. Once the four coefficients of **M** have been determined the growth operator matrix can be progressively powered to identify the rounds of adjustment that are expected to unfold over the subsequent 10 years, 20 years, and so on. If a fixed multiplier σ is used for each adjustment round after time t the future values for population and employment will fall (or rise) depending on how population and employment interact locally. On the other hand, this rather strict assumption could be modified to recognize that each place-specific multiplier σ could shrink, at its own distinctive rate, over the entire study period as some people continued to work while growing older and others took on multiple part-time jobs. In any case, the upcoming analysis will not address this possibility; instead, it will simply identify the point in time when employment is expected to exceed population using the multiplier value that existed at the final year of the estimation period.

To illustrate matters, consider again the four coefficient values estimated for metropolitan Chicago during the period 2005–2015 (see Table 5). In 2015, the values for population and employment (expressed as natural logarithms) were 16.04 and 15.52, respectively, indicating that Chicago's metropolitan population was approximately 9.25 m and its metropolitan employment was 5.50 m at that time. So, in this case, the multiplier $\sigma = 9.25/5.50 = 1.682$, meaning that each worker supported 0.682 other persons (dependents) in 2015. But, applying the growth operator matrix, after 10 years (year 2025), the population and employment levels are projected to be 16.02 and 15.75, respectively, indicating clearly that Chicago's population multiplier is expected to fall through the adjustment process during the subsequent decade 2015–2025. After another 10 years, those figures will shift to 15.99 and 15.89 in 2035, and then to 15.96 and 16.02 in 2045. So, the adjustment process becomes unsustainable sometime between 2035 and 2045; in fact, by interpolation of the two endogenous variables between the appropriate endpoint years, unsustainability in the adjustment process appears to occur sometime between 2041 and 2042. As matters turn out the process is somewhat different for Seattle. Here the projection for population falls much like above but the projection for employment rises much more slowly. Consequently, population must fall a lot for the equalization of population and employment to occur and, in this instance, some sixty years are required before the labor market becomes unsustainable. In other words, even when solutions are stable, the property of sustainability will vary a lot from one metropolitan place to the next.

5.4. Contextual Variables

This portion of this paper makes a few closing observations about the regional variation in the elasticity estimates for the different contextual variables. All the results are based on the eight BEA regions, and it should be clarified that these state groupings are somewhat different from those used by the U.S. Census Bureau [64,65]. The results, given for the eight conjectured relationships mentioned earlier, are all based on the pooling of the various GWR estimates across the four overlapping time intervals, meaning that $n = 1508$ throughout. It is important to emphasize that these are average estimates of the marginal effects and not average figures for the levels of the eight different exogenous variables. Moreover, the GWR estimates for metropolitan areas in any given BEA region will sometimes be affected by the attributes of metropolitan areas located in different BEA regions. The numbers of metropolitan areas in each BEA region are indicated in the first column of the table and both the two highest and two lowest regional deviations from the national average scores are shown in boldface.

Table 6 shows the averages for the three variables that were expected to affect the reduced-form population equation. As indicated, the appropriate nationwide averages

for these effects were *HAMEN* = 0.1040, *CDDEG* = 0.0025, and *HDGDY* = −0.0398. So, across the 25-year period, metropolitan population grew faster where human amenities were higher, cooling degree-days were more frequent, and heating degree-days were less frequent. All the region-specific averages in Table 6 are standard scores that have been generated using the national estimates, pooled across four intervals, where the overall average is 0.000 in all three instances. Consequently, the human amenity figures of 0.098 for BEA region 1 and −0.216 for region 4 indicate that this effect was, on average, somewhat stronger than the national norm in New England but was, on average, much weaker than the national norm in the Southwest. The bottom row indicates a positive estimate for the coefficient so better human amenities generated population growth in New England but restricted population growth in the Southwest. Evidently, human amenities were especially important in New England (0.098), the Southwest (−0.216), the Plains (0.204), and the Rocky Mountain (−0.174) states. These numbers suggest that metropolitan areas in BEA regions 4 and 7 could enhance their population growth even more if human amenities such as restaurants and public goods such as education were improved.

Table 6. Pooled Standard Scores for the Four Population Equations.

Region	Name	*HAMEN*	*CDGDY*	*HDGDY*
1 (15)	New England	**0.098**	**−0.197**	**−0.326**
2 (41)	Mideast	0.055	−0.045	0.085
3 (121)	Southeast	0.000	−0.007	0.005
4 (39)	Southwest	**−0.216**	**0.234**	**0.112**
5 (59)	Great Lakes	0.069	0.002	0.012
6 (33)	Plains	**0.204**	**−0.197**	**−0.236**
7 (22)	Rocky Mountain	**−0.174**	**0.227**	**0.091**
8 (47)	Far West	−0.045	−0.044	0.031
Nation	Base Score	0.000	0.000	0.000
(377)	Actual Estimate	0.1040	0.0025	−0.0398

Note: All figures are averages (*n* = 1508) where national mean is 0.000; numbers of metro areas shown in parentheses.

This table also shows those regions where the population effects of cooling degree-days and heating degree-days were most important between 1990 and 2015. Across the entire nation, *CDGDY* had a small, positive effect on those population numbers, while *HDGDY* had a moderate, negative effect. The Southwest (0.234) and Rocky Mountain (0.227) states both enjoyed considerable population growth even though their summers could be very hot; but, at the same time, New England (−0.197) and the Plains (−0.197) suffered. This same pattern is seen for the more significant winter effect, where the Southwest (0.112) especially benefitted in population growth, while New England (−0.326) especially suffered.

The appropriate estimates for the four overlapping employment equations are shown in Table 7. After noting the overall negative effect induced by marginal wage shifts (note −0.1962 in the bottom row), the job numbers in New England (0.131) rose when that small region's wages were higher but, under the same expansionary conditions, those job numbers fell a lot in the Far West (−0.147). New England (0.084) and the Far West (0.110) especially benefitted from the youthful age composition of their workforces but, on this measure, the Great Lakes (−0.101) and Plains (−0.063) clearly suffered. On the other hand, the Mideast and Great Lakes benefitted jobwise from the professional qualities of their workforces, and here New England and the Far West suffered. Patenting, while being the least important national factor (note 0.0056 in the bottom row), was responsible for some employment growth in the Far West (0.126) and Mideast (0.090); and, despite the presence of high-tech Austin and Boston in those two regions, the Southwest and New England exhibited negative patenting effects. Finally, self-ownership was clearly a factor in the job growth witnessed across the Far West (0.097), Mideast (0.034), and Southeast (0.025) but

this factor was not so important in the Southwest (−0.064), Plains (−0.055), and Rocky Mountain (−0.061) states.

Table 7. Pooled Standard Scores for the Four Employment Equations.

Region	Name	WAGES	PWFOR	PROFS	PATEN	PROPR
1 (15)	New England	**0.131**	0.084	**−0.244**	**−0.153**	**−0.118**
2 (41)	Mideast	**−0.053**	−0.028	0.082	**0.090**	0.034
3 (121)	Southeast	−0.032	0.003	0.022	0.028	0.025
4 (39)	Southwest	**0.093**	0.004	0.003	**−0.218**	**−0.064**
5 (59)	Great Lakes	0.076	**−0.101**	**0.093**	−0.005	−0.026
6 (33)	Plains	0.039	**−0.063**	**−0.114**	0.000	−0.055
7(22)	Rocky Mountain	0.077	**0.084**	−0.013	−0.089	**−0.061**
8(47)	Far West	**−0.147**	**0.110**	**−0.084**	**0.126**	**0.097**
Nation	Base Score	0.000	0.000	0.000	0.000	0.000
(377)	Actual Estimate	−0.1962	0.2898	0.0704	0.0056	0.1246

Note: All figures are averages (n = 1508) where national mean is 0.000; numbers of metro areas shown in parentheses.

As a last exercise, these standard score averages were examined for their geographic variation. Three different cluster analyses were undertaken to discern whether the BEA regions could be consolidated into even larger regions that maintained some uniformity in their metropolitan estimates. In order, these adopted the population effects from Table 6, the employment effects from Table 7, and the combined population and employment effects from the two tables. The Southwest and Rocky Mountain regions grouped together on all three occasions and the Mideast, Southeast, and Great Lakes regions also grouped together on all three occasions. In both instances, the designated BEA regions were contiguous so, clearly, two very broad megaregions accounted for the various effects seen across five of the nation's eight BEA regions. Between 1990 and 2015, New England and the Plains region exhibited similarities in their population effects but not in their employment effects, and the Far West was an employment outlier.

6. Concluding Remarks

To date, the adjustment models addressing joint population and employment change across U.S. metropolitan areas have adopted ordinary least-squares (OLS) regression, an approach that generates global estimates. Alternatively, this paper has adopted geographically weighted regression (GWR) to generate local estimates of population and employment change between 1990 and 2015. Here population is driven by human and natural amenities and employment is driven by wages, patents, self-employment rates, and various facets of the workforce. Other variables were estimated by OLS regression in earlier studies but, to maintain only a small number of key explanatory variables, these were omitted from the current GWR study.

The GWR approach exposed substantial variation in the composition of the 2 by 2 growth operator (endogenous) matrix across the 377 metropolitan places at four different points in time. Nevertheless, in the great majority of cases, a long-run equilibrium was shown to occur, although, especially during the past crisis period 1995–2010, various solutions were unstable. However, the GWR estimates indicated different local adjustment speeds which, in turn, led to notable differences in the attributes of the place-specific convergence processes. Consequently, the various metropolitan areas were projected to have different employment-to-population ratios once those stable states were reached. Moreover, the local estimates revealed that many of the projections might not be sustainable. Whenever employment numbers exceeded population numbers in subsequent periods, the labor markets of these economies would cease to be sustainable.

Future research using a location-specific adjustment model could address a wide variety of topical and methodological issues, and some of these might be explored once the Census 2020 results arrive. First, other approaches, such as the spatial expansion method, could be used to provide local estimates of the 2 by 2 growth operator matrix. Consistency in the results would certainly enhance confidence in the findings of this paper. Second, different versions of GWR could be estimated to clarify how sensitive the findings of this paper are to the version that was chosen. Specifically, some exogenous variables might only have local effects, while other such variables might exhibit global effects. It makes sense that those variables that can be modified by public policy (e.g., human amenities, wages) should have local effects but others (especially natural amenities) might only have global effects. A third issue worthy of more study concerns the nature of the matrix projections. As already noted, it is natural for dependent populations (young and old) to change in relative size, on a local basis, and this factor could be endogenized in a better methodology for establishing those future years when sustainability might grind to a halt. Perhaps this approach could even be wedded with another, one having more demo-economic complexity, to allow metropolitan in- or out- migration to proceed whenever some triggering mechanism—either the dependency ratio or the unemployment rate—became too large or too small [32].

There is also merit in replicating this study using all contiguous counties in the lower 48 states instead of metropolitan areas, or even in clarifying the different location-specific effects that arise in small versus large metropolitan areas [30] Here it must be remembered that changing the numbers of metropolitan areas—perhaps to the top 100 monitored by the Brookings Institution—will also change the underlying spatial structure of the estimation problem [66]. Furthermore, if population and employment levels are replaced by densities very useful insights might arise regarding the very recent tendency for many households to substitute large suburban or micropolitan dwelling units, having longer commutes (if required), for the small inner-city units that offered them superior access to jobs and human-created amenities.

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