Road to Despair and the Geography of the America Left Behind

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Abstract: President Trump's election highlights US economic disparities, especially in rural America. This study assesses 21st century economic conditions to identify broad forces underlying the uneven economic performance of US counties, stressing factors that may be important for lagging regions. We examine the effects of three groups of variables (economic, social/demographic, and geography) on job growth, poverty, and median income. To this end, we split the time period before and after the Great Recession and use standard regression analysis augmented by quantile regressions to assess the heterogeneity in economic performance. The results suggest an increasing role played by economic factors including the benefits of having a fast-growing industry structure. Perhaps more importantly, measures of economic dynamics—the ability of a local economy to "rewire" by reallocating resources in response to economic shocks—emerge as important predictors of performance.

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The United States has always experienced spatial differentials in economic activity and wellbeing. Yet, structural changes such as deindustrialization, technological change, and globalization has led to a perceived widening of spatial income differentials such as declines in Rustbelt, coal country, and much of rural America. The uneven recovery from the Great Recession has further fueled perceptions that large regions are being left behind. Meanwhile, the US has come under grips of a wrenching opioid crisis and related "deaths of despair" that are often associated with the lack of economic opportunity (Betz and Jones 2018; Case and Deaton 2015; Goetz and Davlasheridze 2018). In conjunction, rising income inequality has led many Americans to question whether they will be as well off as their parents (Chetty et al. 2014). The growing angst in stagnating regions is often credited as a key reason for President Trump's surprising 2016 victory (Goetz et al. Forthcoming).

As the country is deeply divided economically and culturally, it is important to identify the general processes that underlie the recent trajectories of US regional development. Understanding the underlying forces would help in shaping policy responses to bring the localities left behind back to the table of economic opportunity and growth. Indeed, this is consistent with calls to depart from development strategies that were ineffective pre-recession and to identify new approaches to be used after the Great Recession (Fodor 2012).

To this end, we examine the effects of three main socioeconomic groupings of factors that reflect different aspects of a locality's economic structure, social/demographic attributes, and natural amenities, as well as position within the urban-rural hierarchy. The selection of the three general variable groupings follows from the economic development literature (Beyers 2013; Partridge 2010; Rupasingha, Goetz and Freshwater 2002). To address whether the period after the Great Recession represents a structural shift in regional dynamics, we further divide the data into pre-recession (2000-2007), recession (2007-2010) and post-recession (2010-2015) periods. We then investigate the changing importance of each factor in explaining employment growth, change in poverty rates, and median household income growth for US counties.

In developing our models, we supplement more traditional (mainly) “static” economic measures with novel measures that approximate the dynamism of a local economy and the ability of a county to *rewire* by reallocating employees from shrinking to expanding sectors. We use cross-sectional regression analysis augmented by first-difference analysis to understand contemporary determinants of local economic well-being and whether the Great Recession altered this relationship. Finally, we use quantile regressions to assess the presence of heterogeneity in the economic relationships between the most and least prosperous locales.

Our results suggest some changing structural relationships between the three explanatory groupings and economic outcomes. We find that the role played by county industrial composition (if it is fast- or slow-growing) is of increasing importance. Also, another increasingly important factor is the local labor market’s ability to “rewire” by facilitating the movement of workers across industries and occupations in response to changing economic conditions. Interestingly, after the dynamism of a local economy is accounted for, industrial diversity is insignificant, suggesting that diversity’s role in stabilizing and promoting growth in local communities (Hammond and Thompson 2004; Watson and Deller 2017) may be working more through labor-market flexibility. Some of our most policy-relevant finding comes from the quantile analysis of differenced job growth. For counties that are lower at the distribution of the response function, the labor-market measures of flexibility emerge as important predictors of growth, suggesting that removing barriers to flow of resources within lagging economies might be a viable policy option.

In what follows we start with a brief descriptive analysis to ascertain that economic well-being is diverging geographically. Concluding that there are good reasons to believe so, we follow with a short literature review. We next describe the data and empirical specifications followed by the empirical results. We separately discuss the results for poverty (and median household income growth to a lesser degree) and job growth. The paper finishes with our concluding thoughts and policy suggestions.

Is Basic Economic Well-Being Diverging?

Since the Great Recession, there is a growing sense that some places are being left behind. Yet, this flies against conventional economic wisdom from neoclassical growth theory that regional incomes have been converging since the Civil War (Barro and Sala-i-Martin 1990). To investigate, using US Bureau of Economic Analysis (BEA) data, we calculate the average standard deviation in per-capita income for each year between 1969-2016 (standardized by national per-capita income) for US states and counties. Specifically, we calculate unweighted standard deviations that reflect differences across space and standard deviations weighted by population to show spatial differences for the average person (which is national income inequality minus the within-state/county component of inequality). The results are plotted in figure 1 where the left panel shows unweighted standard deviations for states and counties, and the right panel shows corresponding standard deviations weighted by population.

Figure 1 shows that analysis at the state level masks considerable within-state inequality. Turning to the county-level results, the unweighted standard deviations show a slight downward trend until 1994, falling to about 0.17 before rising almost 50% to 0.25 in 2014, then falling back to 0.23 in 2016. The population-weighted standard deviations illustrate an even stronger upward trend. After falling slightly to about 0.20 in 1976, the weighted standard deviation steadily increases to about 0.32 in 2016, or a rise of about 60%. The analysis was repeated by removing transfer payments and the divergence pattern for the resulting “market per-capita” personal income is even more striking, further suggesting that economic opportunities are increasingly geographically unequal (not shown). We also did the same using the unweighted and weighted standard deviations of annual wage and salary job growth. There, the trend is steady convergence of job growth rates until 2010. After which, there has been about a one-third increase in the unweighted variation between 2010-2016, though the weighted standard deviation had a more modest increase (not shown). Overall, in terms of income, there has been a steady increase in divergence for nearly 25 years. The divergence in job growth is much more modest, though the post-recession period represents a departure from the pre-recession trend of convergence. The implication is that there are reasons to believe that some regions are increasingly lagging.[i]

<Figure 1 here>

Literature review

The literature investigating the determinants of regional economic growth is enormous; it highlights many factors that are important for local socioeconomic wellbeing across space and time. Such factors can be generally grouped into several broad categories[ii] related to the presence of certain industries and related structural metrics such as (1) industry diversity (Watson and Deller 2017), (2) human capital and innovation (Faggian and McCann 2008; Fallah, Partridge and Rickman 2014; Goetz and Hu 1996), (3) population demographics (Stephans and Deskin 2018; Amcoff and Westholm 2007), (4) culture, social capital and related factors (Akçomak and Ter Weel 2009; Rupasingha, Goetz and Freshwater 2002; Rupasingha, Goetz and Freshwater 2000), and (5) amenities (Deller, Lledo and Marcouiller 2008; Deller et al. 2001) among others. The performance of rural and remote regions have been further defined by remoteness and access to agglomeration (Andersson and Lööf 2011; Partridge et al. 2007; Partridge et al. 2009).

The Great Recession threw the US economy from its long-term growth trend and further intensified scholarly debates on the determinants of regional economic growth. The central topic has increasingly moved to the notion of resilience—i.e., the ability of regions to withstand and recover from shocks. Aside from a concerted effort to operationalize and measure resilience, the discussion focuses on the same broad categories described above (Martin, Sunley and Tyler 2015). The economic resilience literature suggests that the Great Recession revealed many underlying discrepancies in regional economic fundamentals, speeding up the process of divergence in economic fortunes that could be undetectable during prosperous times (Lagravinese 2015). Some researchers note that the Great Recession weakened the regions that lacked strong engines of growth (Martin, Sunley and Tyler 2015) and exacerbated the long-simmering economic and social problems in rural and lagging communities. Others believe that the Great Recession was a watershed for the US economy (Florida 2009; Gore 2010), implying that the nation will need the new ways of resource allocation to respond to a rapidly changing world.

When one thinks about economic resilience as an adjustment process to a shock, the economic variables currently used in the literature may be insufficient, as they focus on a structure of a local economy (e.g. Lagravinese 2015) and generally ignore the dynamics of how a local economy readjusts and rewires. Thus, a key goal of our study is to develop new dynamic measures of local economic adjustment and to assess their effects on economic outcomes.

The literature also points to an important role played by various social/demographic factors in defining regional performance. For instance, the importance of human capital in affecting economic growth is well established (Lucas, 1988; Nelson & Phelps, 1966). Other research points to the local racial and ethnic composition as important for social and economic wellbeing. For example, Easterly (2001) and Partridge and Rickman (2005) find that high-poverty places in the US tend have greater minority populations.

Putnam, Leonardi and Nanetti (1994) stress the role of social capital in regional socioeconomic outcomes. The level of social capital in a community is generally related to participation in associational activities and trust. Several empirical studies find a positive effect of social capital on a range of economic growth indicators in the US (Rupasingha, Goetz and Freshwater, 2000; 2002).

Finally, amenity-led economic development has received significant scholarly attention (Green et al. 2005). Many high-amenity places have been able to capitalize and attract in-migration, even to rural areas (Partridge 2010), although it is unclear how the Great Recession and housing bust affected the long-run prospects of high-amenity locales.

Empirical implementation, data and variables

We start our analysis with a descriptive look at changes in poverty and job growth pre- and post-recession followed by cross-sectional regressions for the post-recession period (2010-2015). This represents our initial exploration of the key factors driving county-level job growth and poverty rates. Of course, cross-sectional approaches can suffer from omitted variable bias. Thus, in the next step we repeat the analysis using a differencing strategy in order to account for time-invariant unobservable factors and to benchmark the post-recession dynamics against the pre-recession period (2010-2015 minus 2000-2007). This allows us to appraise whether the Great Recession led to structural change. We then estimate corresponding models by differencing out the recession years (2010-2015 minus 2007-2010) to isolate changes that occurred since the recession. Finally, to assess heterogeneity among fast- and slow-growing locals, quantile regression of the differenced models is used to estimate changes at the 10th, 50th and 90th percentiles of the conditional distribution of the dependent variable. The analyses are performed using data for over 3,000 counties in the continental US (1,986 nonmetro and 1,052 metro). All models are estimated separately for nonmetro and metro counties to avoid aggregation bias and to account for differing levels of agglomeration.

Cross-Section "Level" Equations for 2010-2015

The cross-sectional model for the 2010-2015 period is shown in (1):

$$Y_{c\tau} = \beta_0 + \beta_1 \boldsymbol{ECON1}_{c\tau} + \beta_2 \boldsymbol{ECON2}_{ct} + \beta_3 \boldsymbol{SOC}_{\mathrm{ct}} + \beta_4 \boldsymbol{GEOG}_c + \boldsymbol{X\beta} + \theta_s + \varepsilon_{c\tau} \qquad (1)$$

where *c* denotes county, τ is a time period from time *t* to time *t1*, and subscript *s* indicates state. The error terms $\varepsilon_{c\tau}$ are clustered by BEA economic areas to account for spatial autocorrelation. Our discussion focuses on the 2010-2015 results, though we briefly review corresponding models for the 2000-2007 pre-recession and the 2007-2010 recession periods (the results are in the Appendix).

The two dependent variables are the 2010-2015 annual (average) change in the poverty rate and the 2010-2015 annualized job growth. Since our sample periods have different durations, we use annualized and average measures to maintain comparability. The vectors ***ECON1***, ***ECON2***, ***SOC***, and ***GEOG*** refer to economic indicators measured over the period under consideration, initial-period economic indicators (measured at the beginning of the period), initial-period social indicators and the county's geographical attributes, respectively. Using explanatory variables at their beginning levels should alleviate reverse causality concerns, though omitted variable bias may still exist. To be sure, our key economic variables should be exogenous as described below. The vector ***X*** comprises a set of controls and θ_s are state dummies to capture the role of state-specific policies on growth and other factors fixed for each state.

The average annual change in the poverty rate is calculated by dividing the change in poverty over the whole period by the number of years, whereas annualized job growth is calculated using the compound annual growth rate formula[iii]. The poverty data are from the Small Area Income and Poverty Estimates (SAIPE) program and employment is from US Census Bureau County Business Patterns (CBP). Note that CBP data do not include government employment, which means that our results are most applicable to the private sector.

In addition to several traditional economic measures used in the literature, we include a set of relatively novel variables that approximate the degree of rewiring of the local economy, which, taken together, constitute the ***ECON1*** and ***ECON2*** vectors in Equation (1). Starting with ***ECON1***, the industry mix variable, *IndMix*, is the predicted growth rate of county employment if all its industries grow at corresponding national growth rates. This measure is sometimes called the Bartik instrument (Bartik, 1991) and is routinely used as an *exogenous* instrument for employment growth. Rather, we are using it as an exogenous measure of demand shocks that arise from each local area having different industry compositions (Betz and Partridge 2013; Tsvetkova, Partridge and Betz 2017). Equation (2) shows how *IndMix* is calculated:

$$IndMix_{c\tau} = \sum_{i=1}^{N} Sh_{cit} NatGr_{i\tau} \qquad (2)$$

where all subscripts are identical to above with subscript *i* indicating industry at the 4-digit NAICS level and there are *N* industries. Sh_{cit} is the share of industry *i*'s employment in county *c* at the beginning of the period τ and $NatGr_{i\tau}$ is the annualized national industry growth rate over the period. Because national growth rates and initial industry shares are used, industry mix is typically assumed to be exogenous. This condition is true as long as there are no labor supply responses associated with lagged industry composition aside from labor supply variables we already control for (reducing any labor supply factors in the residual correlated with lagged industry composition).

One limitation of the CBP is that it has numerous data suppressions when the Census Bureau is concerned that individual firms can be identified in the data. Generally, suppressed values are predominantly found in the information for smaller rural counties. Thus, we use CBP four-digit level data after a linear programming algorithm estimates the suppressed values. The source for these data is the Upjohn Institute for Employment Research that uses the Isserman and Westervelt (2006) algorithm in constructing the data.[iv]

The *JobsFlow* variable is a measure that approximates the expected ease of finding a job in a different industry if one is displaced from work. The variable takes into account job-to-job flow information at the 2-digit NAICS level from the US Census Bureau Longitudinal Employer-Household Dynamics (LEHD) program and industrial composition of a county at the beginning of a period as reflected in the CBP. It is calculated as follows.

$$JobsFlow_{ct} = \sum_i \sum_j Sh_{cit} Sh_{cjt} Flow_{ij} \qquad (3)$$

where Sh_{cit} is county *c*'s share of employment in the *origin* sector *i* at time *t*, the beginning of a period under consideration; Sh_{cjt} is county *c*'s share of employment in the *destination* sector *j* at time *t* and $Flow_{ij}$ is the percent of total employment leaving sector *i* that ends up in sector *j* as reflected in the LEHD. Thus, for each industry × industry pair, the larger the size of the job flow $Flow_{ij}$ from industry *i* to industry *j*, the easier it should be to move between the two sectors if there are job losses or growth in either sector. The sectors are defined at the 2-digit NAICS level and circular flows within a sector are excluded, i.e. when calculating (3), $i \neq j$. Because the job flow data is at the national level, like the industry mix term, it should be exogenous. The CBP is the data source for employment shares used in calculations.

The next two measures, *OccEmpMobility* and *IndEmpMobility*, approximate the dynamics (changes) in a local economy over period τ as evidenced by moves of employees across industries and occupations during the period (Levernier, Partridge and Rickman 2000). It follows the logic of dissimilarity index used in research on racial segregation and diversity (Ellis Wright and Parks 2004) but instead of differences in a locality's racial composition, it captures dissimilarity in employment distribution at the beginning and the end of a period. The measures show the percentage of total county employment at the end of a period that needs to move to other industries or occupations, respectively, in order for the industrial/occupational composition of the local economy to be the same as at the beginning of a period. A greater number suggests that a larger share of workers switched industries or occupations during the period. Equation (4) shows the index:

$$EmpMobility_{c\tau} = \sum_i |Sh_{ict1} - Sh_{ict}| \qquad (4)$$

where *i* refers to an industry at the 4-digit NAICS level and all other subscripts are defined as before. The CBP is the data source for *IndEmpMobility* whereas a proprietary data set from Economic Modelling Specialists, Intl. (EMSI)[v] on the county-level employment by occupation is used to derive *OccEmpMobility*.

Also included in the ***ECON2*** vector is an industry diversity measure, *IndDiversity*, which is calculate as follows using the EMSI data:

$$IndDiversity_{c\mathrm{t}} = 10{,}000 - \sum_i Sh_{cit}^2 \qquad (5)$$

where Sh_{cit}^2 is a squared share of employment in industry *i* (at 4-digit NAICS level) in county *c* in year *t*, which is the beginning period τ. Subtracting the summed squared shares from the maximum possible value ensures that the larger values of *IndDiversity* correspond to a more diverse industry structure. The general expectation is that industry diversity is associated with better economic outcomes because shocks to one sector are less likely to lead to adverse aggregate outcomes. In more industrially diverse economies, average share of a single industry or a sector tends to be smaller meaning that it would be easier for its former workforce to find jobs elsewhere (Hammond and Thompson 2004; Watson and Deller 2017).

The last two variables included in the vector of economic factors are a share of manufacturing in total county employment, *ManufShare*, and a share of labor-intensive (low-wage) manufacturing, *LowWageManufShare*[vi] calculated using the EMSI data. We use deep lags of this variables in our models to mitigate potential endogeneity concerns, i.e. the 2000 share of manufacturing is used in the equations that refer to 2010-2015 and the 1990 share of manufacturing is used in equations that focus on the Great Recession and pre-Recession periods.[vii]

Including manufacturing shares in our models accounts for the general decline in the sector's employment dating to the 1970s, which suggests that more manufacturing-intensive places may be economically struggling. Aside from general manufacturing, labor-intensive manufacturing is particularly exposed to low-wage manufacturing import competition from places such as Vietnam and China (Autor and Dorn 2013), although empirical estimation results for *LowWageManufShare* are usually statistically insignificant.[viii] To further account for susceptibility of a county to differing global and commodity market trends, we control for the deep-lagged 1990/2000 employment shares of agriculture, and mining (these two variables are not reported for brevity). Farm and mining communities are exposed to commodity boom/bust cycles, labor-saving technological change, and technological innovations such as hydraulic fracturing. Because we use deep lags of these variables, EMSI data are used in their calculation.

The ***SOC*** vector includes variables that reflect the county's social characteristics. The first is a measure of social capital, *SocialCap*, using the approach developed by Rupasingha and co-authors (Rupasingha, Goetz and Freshwater 2000; 2002). The social capital measure is derived from community and individual factors that are related to the propensity of residents to participate in associational activities. Such factors include the county's prevalence of membership organizations, voting in presidential elections, and participating in US Census Bureau surveys. The data source is http://aese.psu.edu/nercrd/community/social-capital-resources for the year that most closely corresponds to each specific model[ix]. For example, for the 2010-2015 level equations in (1), we use the lagged 2009 social capital values.

Measures of the level of human capital, racial composition and the 1960 poverty rates are also included in the ***SOC*** vector. The two educational attainment measures are the share of adults with less than high school diploma, *%LessHS*, and the share of adult population with a bachelor degree or higher, *%BA*. There is a long literature that suggests that having a higher initial share of college graduates, for example, is associated with significantly faster local growth in the ensuing decades (Simon 1998; Simon and Nardinelli 2002). In particular, we are interested if greater human capital is a positive force in recovering from the Great Recession that improves a local community's resilience after acounting for other local characteristics.

The models include the shares of population that are African-American, Native American, Asian and of other races to account for social and labor market effects (e.g., discrimination). For brevity, we do not report the racial and ethnic variable results. All education and race variables are lagged to mitigate endogeneity concerns, i.e. the 1990 measures are used in models for the 2000-2007 and 2007-2010 periods and the 2000 measures are used in models covering the 2010-2015 period. Finally, the 1960 poverty rate is included to test for the long-lasting legacy of poverty, which can also be empirically related to the quality of local institutions. The data for all variables come from the US Decennial Census, in which the 1960 poverty measure is from a special Census tabulation for the USDA Economic Research Service.

The geographical attributes include distance to the population-weighed centroid of a nearby Metropolitan Statistical Area (MSA) (a distance to the population-weighed centroid of own MSA for metro counties) and incremental distances to MSAs of increasingly larger sizes (population of at least 250, 500 and 1,500 thousand in 1990) following the logic of Central Place Theory as described by Partridge et al. (2008). The distances are calculated using ArcGIS software. We include these variables to assess whether access to the urban center had differential effects post recession as accessibility is a key feature for rural commuting, while in metro settings, the housing crisis differentially affected exurban and suburban areas. For brevity, we display estimation results for the distance to the nearby MSA, *NearMSAkm*, only. Proximity to the Great Lakes, Pacific and Atlantic oceans (within 50 miles) is captured by dummies *GrtLakes*, *PacificOcean* and *AtlanticOcean* to reflect their roles as amenities. For brevity, these three variables are not reported in the tables below. Using the USDA 1 (low) to 7 (highest) natural amenity classification (https://www.ers.usda.gov/data-products/natural-amenities-scale/), we include individual measures for those valued at 4 (average) to 7 (highest) via inclusion of *Amenity4*, *Amenity5*, *Amenity6* and *Amenity7* indicator variables. This allows us to assess the possible changing role of natural amenities such as for Florida and western Sunbelt regions that were particularly hard hit by the housing bust (Carruthers and Mulligan 2013).

The models also include several common socioeconomic controls used in regional economic analysis. Two population measures account for the effects of agglomeration economies. We include the lagged county population and lagged log population of the nearest (if nonmetro) or own (for metro counties) metropolitan area population as reported by the US Census Bureau. Finally, the cross-sectional level models include state fixed effects to factor out unchanging state-level characteristics that may impact county-level social and economic performance.

Differenced Equations (OLS and Quantile Regressions)

In what will be our base model, to assess differences between the post-recession expansion and the pre-recession expansion, a first-difference model of the dependent and all explanatory variables is employed, except we don't difference the deep-lagged variables (which are still included). The differencing factors out time-invariant unobservables that could potentially bias our level results. Equation (6) is separately estimated for nonmetro and metro subsamples (error terms are clustered at the level of BEA economic areas):

$$\Delta Y_{c\tau} = \beta_0 + \beta_1 \Delta \boldsymbol{ECON1}_{c\tau} + \beta_2 \Delta \boldsymbol{ECON2}_{ct} + \beta_3 ManufEmp_{ct} + \beta_4 LowWageManufEmp_{ct} + \beta_5 \Delta SocialCap_{ct} + \beta_6 \boldsymbol{SOC}_{ct} + \beta_7 \boldsymbol{GEOG}_c + \boldsymbol{X\beta} + \varepsilon_{c\tau} \quad (6)$$

where *c* denotes county and τ is the period from time *t* to time *t1*. The dependent variables are the first differences of (a) annualized employment growth rates for the 2010-2015 period and the 2000-2007 period; (b) average yearly change in poverty rates over the 2010-2015 period and the 2000-2007 period; and (c) annualized median household income growth over the 2010-2015 period and the 2000-2007 period. We repeat the analysis comparing post-recession (2010-2015) to the recession years (2007-

2010), with the results reported in the Appendix (not discussed). The $\Delta \boldsymbol{ECON1}$ vector includes *IndMix*, *OccEmpMobility* and *IndEmpMobility* measures differenced over periods corresponding to the differencing of the dependent variables. The $\boldsymbol{\Delta ECON2}$ vector includes economic variables that are measured at the beginning of each period and are differenced in accordance to the dependent variable differencing, e.g. 2010 value minus 2000 value for our main specification that compares the post-recession and the pre-recession periods. These variables are *JobFlow* and *IndDiversity*. The deep-lagged shares of manufacturing, low-wage manufacturing, agriculture, and mining are used without transformation.

Among social characteristics, only the values of social capital are differenced. All other variables are used in the form identical to Equation (1). The same applies to the geographical attributes that are constant over time. The control variables do not change between Equations (1) and (6) except for the omission of the state fixed effects in the latter because they are differenced away. Because the county fixed effects are factored out, the coefficients in the differenced equations are interpreted as within-county responses to changes in explanatory variables.

The deep-lagged variables have a different interpretation in the first-difference models. The unchanging level effects of these (and all other constant) variables are differenced away in the fixed effects. What is left is the persistent disequilibrium effects of those variables that would likely decrease over time. That is, if those variable coefficients are statistically insignificant, that *does not* mean that the variable has no influence because its constant effects over time could be in the fixed effect that are differenced out of the model. Appendix table A1 summarizes all variables and their data sources, whereas Appendix table A2 shows summary statistics.

Our last step is to explore the heterogeneity of the effects at different points of the conditional distribution of the response function. In particular, we seek to explore the variations in the statistically significant relationships for high-performing *vs.* low-growing counties, in which the OLS model produces responses near the mean/median of the distribution. To do so, we re-estimate Equation (6) using quantile regression for the 10^{th}, 50^{th} and 90^{th} percentiles (we report the 10^{th} and the 90^{th} percentile results only).

Estimation results and discussion

We arrange our presentation of results around the two main dependent variables starting with the average change in the poverty rate with a short discussion of median household income for the differenced models. The estimation results from all three steps (level and differenced equations followed by quantile regression) are presented together. After discussing the poverty and median household income models, we present corresponding results for employment growth.

Change in Poverty Rates

Figure 2 shows geographical distribution of the 2000-2007 average poverty rate change (left panel) and of post-recession dynamics (2010-2015) relative to the presented pre-recession trends (right panel). A visual inspection of figure 2 suggests that during the pre-recession expansion, the West tended to perform better with a modest decrease or no change in poverty (except for counties in Washington and Oregon, as well as in the southwest part of the West North Central Census division), with the mid-Atlantic region and Florida also faring well. However, when comparing the differences in poverty rate changes in the post- and pre-recession periods, there is somewhat of a reversion to the mean. The west of the country fared much worse together with the mid-Atlantic region and Florida after the recession. While the East performed much better in general, note that persistently poor regions such as the Mississippi Delta, southeastern Black belt, and central Appalachia fared worse in both the pre- and post-Great Recession expansions. Yet, the perception that manufacturing-centered regions in the Rustbelt performed poorly after the recession is not supported at least in terms of poverty rates.

<Figure 2 here>

The empirical analysis for the cross-section level model and the first-difference model is presented in Table 1. The results point to differing effects of the three variable groupings. Most generally, measures of economic composition and geographical attributes mainly affect nonmetro counties, whereas social characteristics are statistically important in both the metro and nonmetro samples, with more variables statistically significant in the former.

What stands out in both the post-recession level model and the first-difference models is the important role of whether a county experienced favorable (unfavorable) demand shocks associated with a fast-growing (or slow-growing) industry composition (*IndMix*). However, in some sense, because of the difficulty to change an area's industry composition, the ability of policymakers to influence local poverty in the short-to-medium term is then somewhat limited.

Rural economies tend to lack the scale that typically leads to better labor market matching found in large cities (Rosenthal and Strange 2004). Thus, it seems more likely that having more industry and occupational job mobility would relate to lower rural poverty. Industry mobility is especially associated with lower nonmetro poverty rates in the level models, consistent with positive rewiring effects or resilience. However, in the level models, greater occupational mobility is related to increases in the 2010-2015 poverty rates, indicating that at least at the bottom of the income distribution (where labor mobility is able to affect poverty rates), occupational mobility is downward implying lower pay and worse aggregate performance in terms of poverty measures. In both the metro and nonmetro cross-section models, the other labor-market dynamic variables are statistically insignificant except that greater industry diversity is associated with lower metro poverty over the 2010-2015 period (column 2). In the first-difference models, the dynamic variables are statistically insignificant except for greater occupation mobility is associated with *greater reductions* in metro poverty rates between the two economic expansions (column 4).

Contrary to what may be expected, greater manufacturing share in nonmetro counties is negatively related to poverty rates in both the cross-sectional model (col. 1) and in the change between the two economic expansions (col. 3). One likely explanation is that manufacturing sustained a modest bounce back after the recession that especially helped nonmetro low-wage households. Yet, greater share of low-wage manufacturing was statistically insignificant, suggesting that any poverty-reducing effects were general to all of manufacturing. In metro counties, the two manufacturing share variables are statistically insignificant.

Turning to the other social/demographic attributes, social capital and historical poverty levels are insignificant. Places with greater levels of human capital measured by the share of college graduates enjoyed decrease/smaller increase in metro and nonmetro poverty. However, this could be unexpected, as higher levels of university graduates would normally impact those above the poverty line. A somewhat unexpected result is the two cases in which there is a statistically significant negative association between the share of adults with less than high school degree and changes in the poverty rate.

Regarding the geography variables, being closer to metropolitan areas is associated with higher nonmetropolitan poverty, which is inconsistent with Partridge and Rickman (2008) and may reflect troubles in exurban areas as a result of the housing crash. Similarly, being farther away from the metropolitan core is associated with higher *metro* poverty in the first-difference metro model (col. 4), further suggesting that poor exurban metro households struggled in the wake of the Great Recession and housing bust, though it is not clear if this is a permanent effect. In both the nonmetro and metro cases, the statistically significant distance effects in between the two expansions (cols 3 & 4) suggest that with county fixed effects differenced out, the role of proximity continues to increase, at least in terms of poverty rates. Finally, when considering the relative change in poverty between the two economic expansions (cols 3-4), higher natural amenities are generally related to relatively higher poverty in the latter period, suggesting that those areas were struggling to recover.

<Table 1 here>

As noted above, we do not stress the earlier level models for 2000-2007 and 2007-2010 results (in Appendix tables A3 and A4). Briefly, there is some evidence of changing responses that may be consistent with a structural shift as a result of the Great Recession (Florida 2009; Gore 2010). With exception of the industry dissimilarity index, which is negatively associated with nonmetro poverty, the economic flows and rewiring measures do not emerge as important predictors of lower poverty before the recession (although they all are weakly significant in the nonmetro sample). During the 2000-2007 period it is surprising that both low and high levels of human capital are *positively* related to changes in the poverty rate, in which areas with higher shares of college graduates might have crowded out low-paying jobs. In the recession period, the share of adults with *less* than a high school degree has a positive and significant coefficient in the metro model. Manufacturing share is statistically insignificant before the recession, perhaps because the positive effects of its higher blue-collar wages were offset by its steady pre-recession decline in employment. During the recession, nonmetro counties with greater manufacturing concentration suffered larger increases in poverty rates, consistent with rapid declines in manufacturing employment.

To explore possible heterogeneity across counties with various poverty dynamics, we re-estimate Equation (6) using quantile regression. Table 2 shows estimation results for the 0.1 and 0.9 centiles (for brevity). That is, relative to the prerecession expansion, the 10^{th} percentile results reflect the weakest performers in terms of changes in poverty rates (in reducing poverty), while the 90^{th} percentile results are representative of the performance of those who made the most gains in reducing poverty thereafter. For the most part, these results suggest that at the tails of the poverty rate distribution, the general pattern is one of statistically insignificant coefficients, suggesting that at the tails, the reasons for their relative post-recession performance are mainly idiosyncratic.

A couple key results are unchanged. One is that for the weakest part of the poverty distribution, demand shocks related to their industry mix is (weakly) negatively related to nonmetro poverty. Likewise, *IndMix* remains negative and statistically significant in both the metro and nonmetro samples at the 50th percentile (not reported). Thus, industry composition's positive effects on the ability of a locality to reduce poverty are clearest at the middle of metro distribution and in the lower half (or lower than 90 percent) of the nonmetro distribution. Moreover, a concentration of nonmetro manufacturing is negatively related to poverty in places that did relatively well in reducing their poverty rates relative to the prerecession period. Consistent with the OLS results, higher levels of college graduates are associated with lower metro poverty at both the 10th and 90th percentile, although in the former case the coefficient is significant at the 0.1 level only. Finally, though it is a little weaker in the metro case, high natural amenities locations tend to have higher poverty rates across the distribution. Yet given the overall general insignificance of most coefficients, there is no special formula from the best performers that one could point to in reducing poverty, though there is evidence that for those who are weaker performers in the poverty distribution, a high-growth industry composition might be associated with better performance.

<Table 2 here>

Overall, our poverty results suggest that a locality's industry composition is one of the most important determinant in alleviating poverty. In the differenced analysis, which is our main focus, the industry mix term and manufacturing shares in nonmetro counties are more important in reducing poverty *after* the recession compared to the pre-recession expansion, although the *IndMix* variable seems less relevant at the ends of poverty performance distribution among counties. In metro counties, increased occupational mobility has positive effects too; this result holds for both low- and high-performers in terms of poverty alleviation after the recession compared to the pre-recession period.

Median Household Income Growth Rates

As noted above, we briefly discuss the median household income growth results for the first-differenced post-recession/pre-recession models shown in the far-right panel in Table 1. Besides space limitations, a key reason for the brief discussion is that the median household income results are in many ways a mirror image of the poverty results. Industry-mix demand shocks are positively related to median household income growth, again supporting industry composition's key role in well-being. As in the quantile regression results for the poverty rate models, industry composition is a particularly important growth determinant at the middle of distribution (not shown). Unlike the poverty results, however, growing industry composition is also a strong predictor of income growth in low-performing metro counties (the variable is insignificant in counties with the best relative median household income gains).

For nonmetro areas, greater occupation and industry workforce mobility is associated with higher median household income growth. Manufacturing concentration appears to promote faster median household income growth relative to the pre-recession expansion in both county types. In the nonmetro model, high amenity areas had lower income growth, which may reflect weak post-recession economies, though it could reflect a compensating differential in spatial equilibrium. Conversely, the amenity variables are only weakly significant in the metro model.

Employment Growth Rates

Figure 3 shows the changes in the geographical pattern of job growth before and after the Great Recession. The left panel plots annualized employment growth rate during the 2000-2007 period, while the right panel presents the difference between the pre-recession and post-recession periods. The spatial patterns of job growth are visually consistent with poverty performance reported in Figure 2 in that regions that had less job growth generally had higher poverty rates. The seeming reversal of this pattern in the right-hand-side panel again suggests that the West fared better pre-recession, with the East faring relatively better post-recession. In particular, job growth in the Great Lakes region generally accelerated. The relative post-recession improvement for much of the Rustbelt is surprising in light of the strong performance of President Trump in the 2016 election and the associated public discussion thereafter.

<Figure 3 here>

Table 3 reports the estimation results for the cross-section post-recession model and for the differenced model comparing the post- and pre-recession periods. Again, economic factors emerge as important in determining the employment performance of both metro and nonmetro counties. Local economies that experienced positive demand shocks associated with their industry composition enjoyed greater annual job growth rates, where the positive effects are stronger for metro counties. For the level equations results displayed in the left-hand-side panel, employment turnover across occupations and industries (only across industries in the nonmetro sample) are positively related to job growth. Yet, this statistically significant effect only applies to nonmetro counties in the first-difference models between the two expansions (col 3). While the ease for workers to change sectors (*JobsFlow*) has a statistically insignificant coefficient in the level models, its effects become positive and statistically significant when differencing out the fixed effect (cols 3-4). Conversely, having a greater diversity of industries is statistically insignificant across all models. Manufacturing share is positively related to nonmetro job growth in the 2010-15 equation but when subtracting the pre-recession period, this effect is statistically insignificant. However, there is no statistical evidence that concentrations of manufacturing reduce employment growth. It is unclear whether this is just a post-recession bounce back but it does weakly suggest that manufacturing is currently associated with lower rural poverty.

To summarize estimation results for the economic grouping of variables, economic structure that affords more opportunities for labor to change industries and occupations, especially in nonmetro counties, emerges as an important factor for areas to outperform their pre-recession performance in job growth. That is, economies that more successfully rewired are the ones in which it easiest for workers to shift to growing firms. This factor appears to be more important than before the crisis. Interestingly enough, after accounting for industry composition using employment shares, as well as for the intensity of employment dynamics and inter-sectoral flows, industrial diversity (commonly believed to be an important determinant of economic growth) is consistently insignificant. Most likely, these results suggest that it is not diversity *per se* that matters but the degree to which the industrial structure of a local economy facilitates flows of employees and other resources across industries and occupations.

In terms of the social variables, the 2010-2015 level models (cols 1-2) point to a positive relationship between employment growth and higher levels of human capital measured by the share of college graduates. This education result does not hold in the differenced models, perhaps because the impact of human capital is totally captured by the fixed effects. It is interesting that in the differenced models (cols 3-4), historically-high (1960) poverty counties have less job growth, even after fixed effects are differenced away. This result implies a long-lasting negative disequilibrium effect of factors associated with high poverty almost 60 years ago and that these effects persist today. One possible explanation could be that Southern states used to have particularly high poverty rates in 1960. The historical poverty rate variable in our models might pick up the effects of historical institutional factors such as the role of government or even factors associated with slavery.

High natural-amenity places have no different employment growth during the post-recession period compared to their less-attractive counterparts. This result is consistent with the poverty models and suggests that one possible structural change could be the 20th century's amenity-led migration (Partridge 2010) is no longer stoking job growth. However, the amenity results are also consistent with the possibility that high-amenity places (e.g. Florida and California)—which suffered larger declines in the quality of life during the Great Recession (Carruthers and Mulligan 2013)—had a slower recovery from the housing crash and the Great Recession (at least initially).

A comparison of Tables 3, A3 and A4 for the level equations (2000-07, 2007-10, and 2010-15) reveals some changing patterns. One factor that remains somewhat unchanged is that positive demand shocks due to an industry mix is a significant factor associated with more job growth and lower poverty. Although several economic rewiring and dynamics factors are significant before and after the recession, during the recession they are mostly insignificant. One explanation could be that facilitating labor mobility across sectors and occupations has beneficial impacts, but they are not enough to overcome a major downturn across virtually all industries—i.e., there are no places for displaced workers to go to in search of better fortunes. During the recession, it is interesting that more industrially diverse nonmetro economies had less job growth. One implication may be that with a general economic decline, the positive effects of diversity in facilitating employment growth mainly applies to more concentrated shocks such as major plant closing and not to large general downturn that affects all sectors.

<Table 3 here>

We now examine the heterogeneity of the employment responses between fast- and slow-growing counties using the quantile regressions for the first-difference between the two economic expansions (in Table 4). A high-growth industry mix especially supports growth at the 90th percentile. Not only do such counties presumably have a faster-growing industry composition, but they get more “bang-per-buck” from their structure. In the case of slow-growers (left panel), only metro counties benefit from a fast-growing industry mix, in which the metro coefficient is barely just over one-half of the corresponding coefficient at the 90% percentile. Nonmetro poor performers appear to be unable to benefit from a better industry structure, in which they are doubly penalized because such places likely have an unfavourable structure to begin with. Yet, it is especially interesting that at the 10th percentile, metro and nonmetro county job growth is positively associated with the adaptability and rewiring of their economies as measured by the *JobFlow* and *OccEmpMobility* variables.

Although further analysis should confirm and validate this assessment, it appears that targeting industrial development by accounting for the existing industry composition and labor flows among sectors is likely to produce better results in lagging areas compared to attempts to increase industrial diversity or to create clusters *per se*. That is, trying to attract and develop industries that can take advantage of the accumulated expertise of a region and organically blend into the existing local structure facilitating flows of resources appears to lead to greater job growth. Thus, designing industry development strategies that take into account the ability of some industries (given the industrial structure already in place) to complement workforce mobility may be a better tactic than relying on input-output linkages, clusters, or knowledge spillovers that have produced dubious results (Duranton 2011; Feser, Resnki and Goldstein 2008). The results of our analysis are in line with a developing literature in evolutionary economics on the nature of industrial recombination in a region (He, Yan and Rigby 2016; Neffke, Henning and Boschma 2011; Poncet and de Waldemar 2013; Tsvetkova and Partridge 2017).

<Table 4 here>

Conclusion

In this article we explore how various economic, social, and geography factors influence US county economic wellbeing in the 21st century. We do this by splitting the sample into three periods: pre-recession, recession and post-recession. Using a combination of cross-sectional, first-difference, and quantile regression analyses, we try to detect structural changes that possibly occurred during or since the Great Recession in the the determinants of job growth and the change in poverty rates in rural and urban counties. In addition to focusing on demand shocks due to industry mix and other traditional determinants from the literature, we consider several relatively novel measures of labor-market flexibility aimed at measuring the ability of local areas to reallocate workers across industries and occupations.

We present descriptive evidence that suggests that the East's performance during the post-recession expansion improved relative to the pre-recession expansion (including in the Rustbelt), which contradicts the public view that President Trump's victory was driven by frustrated voters in stagnating areas. Given that the economic performance seems to be improving, the wide-spread frustration might stem from the so-called mental anchoring, whereas people might be fixated on the Great Recession decline and ignore the signs of better performance in the recent years.

Our estimation suggests that through the three periods considered, economic factors are important determinants of economic well-being. In general, the primary factor that is almost universally associated with lower poverty and greater job growth (at least in the middle of distribution) is the demand shocks related to county's industry mix—which on the negative side for policymakers implies that once a location's industry composition is set, it is hard to alter its economic growth path. On the positive side, however, there is some evidence that counties exhibiting greater flexibility of their economies, measured by the shifts in employment across industries and occupations or by the propensity of the local industrial structure to accommodate higher intersectoral job flows, often performed better after the recession (especially in rural and areas).

The quantile regression results for differenced employment growth suggest that with the exception of nonmetro job growth at the lower part of the distribution, industry mix demand shocks are key factors driving job growth at both the upper and lower parts of the distribution. Likewise, measures of employment reallocation appear to be most important at the lower end of the distribution (and in rural areas). Conversely, there is weak evidence that having a more diverse industry structure positively affects outcomes, suggesting that once labor-market mobility factors are accounted for, there is little left for diversity to influence economic outcomes. Especially at the lower end of the distribution in terms of job growth, the ability of counties to reallocate labor towards faster growing firms and industries (to rewire) is an important factor behind better performance since the Great Recession. This finding has important policy implications. Rather than simple diversification efforts or efforts to build clusters, our findings suggest that lagging areas should focus more on helping those firms and industries that would facilitate reallocation of labor towards its more productive use.

Of demographic factors, the importance of higher human capital was only modestly confirmed. While more research is needed, the results suggest a smaller role for human capital in determining economic growth. Of course, this could represent some of the adjustment coming out of the Great Recession and may change. The positive effects of natural amenities observed in the 20th century as documented in the literature are mostly reversed during the Great Recession and after, pointing to the limitations of reliance on amenity-led development in US counties. In addition, the decline of amenity-led growth in the 21st century may suggest that at least in terms of spatial equilibrium, amenity migration may have run its course. To conclude, we find that any structural changes are relatively modest with a post-recession shift toward economic factors such as industry composition and away from human capital and amenity-led growth. Yet, in some ways, these modest changes may make it harder for policymakers to even out growth.

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Appendix

Table A1. Brief variable description and sources

Group	Variable	Brief description	Data source(s)
Dependent	*AnnEmpGrowth*	Annualized employment growth in a county	"Unsuppressed" CBP*
	AvPovRateChange	Average yearly change in poverty rate	SAIPE
Economic	*IndMix*	Industry mix term from shift-share analysis; expected growth rate in a county if all its industries grow at the corresponding national growth rates	"Unsuppressed" CBP*
	JobsFlow	A measure of how easy it is to find employment in another sector given county's industrial composition	LEHD, "Unsuppressed" CBP*
	OccEmpMobility	A measure of employment share at the end of a period that needs to shift to another occupation in order for the county's occupational composition to be the same as at the beginning of a period	EMSI
	IndEmpMobility	A measure of employment share at the end of a period that needs to shift to another industry in order for the county's industrial composition to be the same as at the beginning of a period	"Unsuppressed" CBP*
	IndDiversity	10,000 minus Herfindahl-Hirschman index calculated for industry employment shares at the 4-digit NAICS level	"Unsuppressed" CBP*
	ManufShare	Share of employment in manufacturing	EMSI
Social	*SocialCap*	A measure of social capital in a county	Rupasingha et al. (2006)
	%LessHS	Share of adults with less than high school diploma	US Census
	%BA	Share of adults with BA degree	US Census
	%Black	Share of African-American population	US Census
	PovRate1960	Historical poverty rate in 1960	US Census
Geography	*NearMSAkm*	Distance to nearby MSA in kilometers	US Census shape files processed with ArcGIS
	PacificOcean	Indicator for counties within 50 mi of Pacific Ocean	US Census shape files processed with ArcGIS
	AtlanticOcean	Indicator for counties within 50 mi of Atlantic Ocean	US Census shape files processed with ArcGIS
	Amenity4	Level 4 natural amenity index	USDA
	Amenity5	Level 5 natural amenity index	USDA
	Amenity6	Level 6 natural amenity index	USDA
	Amenity7	Level 7 natural amenity index	USDA
Controls	*LabIntManuf*	Share of employment in labor-intensive manufacturing (see Footnote 6 for a list of industries)	EMSI
	AgriShare	Share of employment in agriculture	EMSI
	MiningShare	Share of employment in mining	EMSI
	%Native	Share of Native American population	US Census
	%Asian	Share of Asian population	US Census
	%Other	Share of other races	US Census
	GrtLakes	Indicator for counties within 50 mi of Great Lakes	US Census shape files processed with ArcGIS
	IncDist250	Incremental distance to MSA of at least 250 thousand in 1990	US Census shape files processed with ArcGIS
	IncDist500	Incremental distance to MSA of at least 500 thousand in 1990	US Census shape files processed with ArcGIS
	IncDist1500	- Incremental distance to MSA of at least 1500	US Census shape files

	thousand in 1990	processed with ArcGIS
LnMSApop	Log of 1990 size of the nearby (or own for metro counties) MSA	US Census
TotPop	Own county population in 1990	US Census

* CBP with suppressed data filled using linear programming algorithm (Isserman & Westervelt, 2006)

Table A2. Summary statistics by county type for main periods*

Variable	Nonmetro counties				Metro counties			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Dependent variables								
AnnEmpGrowth	0.84	3.66	-11.31	47.15	1.50	2.56	-31.21	19.09
AvPovRateChange	-0.11	0.43	-3.12	2.79	-0.07	0.35	-1.54	1.52
ΔAnnEmpGrowth	0.50	4.60	-30.00	66.98	0.18	3.69	-56.80	30.03
ΔAvPovRateChange	-0.34	0.49	-3.07	2.52	-0.30	0.44	-2.41	1.21
Explanatory variables: Economic								
IndMix	1.65	0.52	-1.01	5.44	1.70	0.38	-0.93	4.27
JobsFlow	4.09	0.58	0.67	6.68	4.41	0.46	1.48	5.51
OccEmpMobility	12.86	5.97	0.00	87.21	9.87	4.53	2.01	43.43
IndEmpMobility	43.68	17.81	12.25	172.68	33.34	15.93	13.30	177.53
IndDiversity	9,467.4	420.45	2,458.6	9,825.3	9,623.1	378.1	2,509.8	9,865.4
ManufShare	0.12	0.10	0.00	0.50	0.12	0.08	0.00	0.58
ΔIndMix	1.26	1.09	-8.67	7.07	1.23	0.82	-4.01	5.34
ΔJobsFlow	0.03	0.48	-3.34	4.20	-0.03	0.38	-2.34	2.53
ΔOccEmpMobility	-4.63	7.25	-55.04	63.51	-4.20	4.80	-54.36	15.48
ΔIndEmpMobility	-17.25	19.82	-165.96	95.38	-14.65	13.89	-129.28	46.00
ΔIndDiversity	-5.93	198.50	-2,812.42	1,033.6	-2.58	131.93	-1,151.80	1,285.22
Explanatory variables: Social								
SocialCap	0.26	1.41	-3.42	7.07	-0.50	0.95	-3.93	17.44
%LessHS	24.19	8.93	3.67	65.30	19.84	7.53	3.04	49.55
%BA	9.70	3.93	2.58	40.02	13.20	5.64	2.47	36.55
%Black	7.89	14.89	0.00	86.49	10.33	13.45	0.03	80.34
PovRate1960	37.15	16.17	2.16	81.57	29.18	15.62	5.29	78.15
ΔSocialCap	0.00	0.67	-4.81	3.75	-0.01	0.61	-1.67	11.24
Explanatory variables: Geography								
NearMSAkm	96.72	58.02	17.01	408.19	24.50	20.02	0.00	96.87
PacificOcean	0.01	0.09	0.00	1.00	0.03	0.17	0.00	1.00
AtlanticOcean	0.04	0.20	0.00	1.00	0.16	0.36	0.00	1.00
Amenity4	0.31	0.46	0.00	1.00	0.33	0.47	0.00	1.00
Amenity5	0.08	0.28	0.00	1.00	0.07	0.26	0.00	1.00
Amenity6	0.03	0.18	0.00	1.00	0.06	0.23	0.00	1.00
Amenity7	0.01	0.10	0.00	1.00	0.02	0.14	0.00	1.00
Control variables								
LabIntManuf	2.25	4.12	0.02	41.50	1.82	3.33	0.03	43.11
AgriShare	0.13	0.10	0.00	0.62	0.06	0.07	0.00	0.45
MiningShare	0.02	0.04	0.00	0.84	0.01	0.02	0.00	0.31
%Native	1.95	7.00	0.00	85.60	0.76	2.05	0.02	36.88
%Asian	0.41	0.46	0.00	5.81	1.51	2.41	0.00	31.34
%Other	2.49	4.95	0.00	39.06	2.76	4.74	0.03	39.08

GrtLakes	0.03	0.16	0.00	1.00	0.06	0.23	0.00	1.00
IncDist250	68.38	109.32	0.00	621.43	37.02	74.32	0.00	621.56
IncDist500	42.88	65.88	0.00	426.36	36.76	68.20	0.00	490.54
IncDist1500	89.05	111.06	0.00	557.70	91.76	131.31	0.00	599.21
LnMSApop	0.31	2.01	0.00	15.41	9.84	6.04	0.00	16.07
TotPop	24,097	22,606	414	182,193	210,669	463,821	1,771	9,519,338
Observations	1,986				1,052			

* Summary statistics are given for the 2010-2015 level equations and 2010-2015 minus 2000-2007 differenced equations.

Table A3. OLS estimation results for level equations, pre-recession 2000-2007

Explanatory variables	Employment growth		Change in poverty	
	Nonmetro	Metro	Nonmetro	Metro
IndMix	.75***	1.1***	-.031***	-.01
	(0.12)	(0.26)	(0.01)	(0.02)
JobsFlow	.57***	.46	-.023*	-.011
	(0.19)	(0.42)	(0.01)	(0.02)
OccEmpMobility	.056***	5.4e-03	-1.8e-03*	-3.2e-03
	(0.02)	(0.05)	(0.00)	(0.00)
IndEmpMobility	-3.7e-03	.041**	6.8e-04*	-1.9e-04
	(0.01)	(0.02)	(0.00)	(0.00)
IndDiversity	2.5e-04	9.5e-04	1.0e-05	-8.9e-06
	(0.00)	(0.00)	(0.00)	(0.00)
ManufShare	.99	5.8*	-.14	.068
	(1.19)	(2.97)	(0.11)	(0.13)
LowWageManufShare	-.012	-8.1e-03	2.5e-04	4.0e-03*
	(0.01)	(0.03)	(0.00)	(0.00)
SocialCap	-.27**	-.44***	-1.6e-03	4.1e-03
	(0.11)	(0.16)	(0.01)	(0.01)
%LessHS	-.039**	-.12***	6.7e-03***	9.3e-03***
	(0.02)	(0.03)	(0.00)	(0.00)
%Black	-.028***	-.033***	5.7e-03***	3.1e-03***
	(0.01)	(0.01)	(0.00)	(0.00)
PovRate1960	.026***	.079***	-1.1e-03	-9.2e-04
	(0.01)	(0.01)	(0.00)	(0.00)
NearMSAkm	-2.8e-03**	7.7e-03	-8.3e-05	-1.7e-03***
	(0.00)	(0.01)	(0.00)	(0.00)
Amenity4	.35**	.021	-.03	-.018
	(0.17)	(0.18)	(0.02)	(0.02)
Amenity5	.69*	-.072	-.054	-9.9e-03
	(0.35)	(0.33)	(0.03)	(0.05)
Amenity6	.14	-.16	-.059	.026
	(0.55)	(0.34)	(0.05)	(0.05)
Amenity7	1	-1.2***	-.1	-1.5e-03
	(1.38)	(0.35)	(0.09)	(0.05)
Constant	-5	-13**	-.17	9.4e-03
	(4.00)	(5.85)	(0.23)	(0.27)
Observations	1986	1052	1986	1052
R^2	0.246	0.353	0.413	0.391

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors clustered at BEA area level in parentheses; all models include a full set of controls as described in the text (*AgriShare, MiningShare, IncDist250, IncDist500, IncDist1500, %Black, %Native, %Asian, %Other, GrtLakes, PacificOcean, AtlanticOcean*, *LnMSApop*, *TotPop* and state fixed effects).

Table A4. OLS estimation results for level equations, recession 2007-2010

Explanatory variables	Employment growth		Change in poverty	
	Nonmetro	**Metro**	**Nonmetro**	**Metro**
IndMix	.67***	.64***	-.055***	-.045**
	(0.17)	(0.12)	(0.02)	(0.02)
JobsFlow	.19	.24	.044	.041
	(0.38)	(0.28)	(0.04)	(0.04)
OccEmpMobility	.017	-.14***	-1.4e-03	-9.1e-03
	(0.06)	(0.04)	(0.00)	(0.01)
IndEmpMobility	-.011	-.01	-2.7e-03**	-1.6e-03
	(0.03)	(0.01)	(0.00)	(0.00)
IndDiversity	-1.3e-03**	-2.8e-04	6.2e-05	1.7e-05
	(0.00)	(0.00)	(0.00)	(0.00)
ManufShare	-2.2	-.78	.56**	-.01
	(2.00)	(1.65)	(0.28)	(0.29)
LowWageManufShare	.02	2.5e-03	7.5e-03	-4.4e-03
	(0.04)	(0.03)	(0.01)	(0.01)
SocialCap	.069	.051	-.051**	-.019
	(0.16)	(0.11)	(0.02)	(0.02)
%LessHS	-.044	-.065**	-4.6e-03	.015**
	(0.04)	(0.03)	(0.01)	(0.01)
%BA	-.034	-.042	2.7e-03	-3.8e-03
	(0.06)	(0.03)	(0.01)	(0.01)
PovRate1960	.023	.019**	-5.1e-03*	-.01***
	(0.03)	(0.01)	(0.00)	(0.00)
NearMSAkm	5.9e-03**	-2.3e-03	-8.5e-04**	-2.9e-03**
	(0.00)	(0.00)	(0.00)	(0.00)
Amenity4	-4.7e-03	.17	.12**	.017
	(0.29)	(0.19)	(0.05)	(0.05)
Amenity5	.65	-.4	.1	.055
	(0.92)	(0.37)	(0.10)	(0.10)
Amenity6	-.95	-.34	.14	.051
	(0.76)	(0.37)	(0.12)	(0.10)
Amenity7	.47	.63	.069	.092
	(1.06)	(0.45)	(0.14)	(0.13)
Constant	9.5**	3.5	.3	.71
	(4.67)	(2.69)	(0.67)	(0.58)
Observations	1986	1052	1986	1052
R^2	0.223	0.387	0.219	0.269

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors clustered at BEA area level in parentheses; all models include a full set of controls as described in the text (*AgriShare*, *MiningShare*, *IncDist250, IncDist500, IncDist1500, %Black, %Native, %Asian, %Other, GrtLakes, PacificOcean, AtlanticOcean, LnMSApop, TotPop* and state fixed effects).

Table A5. OLS estimation results for differenced equations, 2010-2015 minus 2007-2010

Explanatory variables	ΔEmployment growth		ΔChange in poverty	
	Nonmetro	Metro	Nonmetro	Metro
ΔIndMix	.92***	1.4***	-.092***	-.11***
	(0.16)	(0.16)	(0.02)	(0.03)
ΔJobsFlow	2.6***	.93	-.068	-.083
	(0.85)	(1.29)	(0.08)	(0.12)
ΔOccEmpMobility	.016	-.051	3.1e-03	-4.5e-03
	(0.06)	(0.06)	(0.00)	(0.01)
ΔIndEmpMobility	.025	-.013	-2.5e-03	1.4e-03
	(0.03)	(0.03)	(0.00)	(0.00)
ΔIndDiversity	2.1e-03	-2.5e-03	-1.3e-04	2.3e-04
	(0.00)	(0.00)	(0.00)	(0.00)
ManufShare	3.1	-1.2	-.88**	.048
	(2.50)	(4.60)	(0.36)	(0.43)
LowWageManufShare	-3.7e-05	.019	-.019**	-5.8e-03
	(0.04)	(0.06)	(0.01)	(0.01)
ΔSocialCap	.62*	.086	-.11**	-.065
	(0.36)	(0.49)	(0.05)	(0.09)
%LessHS	.017	.036	4.4e-04	-.016**
	(0.03)	(0.03)	(0.01)	(0.01)
%BA	-.034	.1***	-5.4e-04	-1.5e-03
	(0.06)	(0.03)	(0.01)	(0.01)
PovRate1960	-.033	4.0e-03	7.5e-03**	5.2e-03*
	(0.02)	(0.01)	(0.00)	(0.00)
NearMSAkm	-5.7e-03	9.0e-03	3.7e-04	4.7e-03***
	(0.00)	(0.01)	(0.00)	(0.00)
Amenity4	.51*	-.21	-.17**	-.054
	(0.28)	(0.30)	(0.07)	(0.06)
Amenity5	.69	1**	-.16	-.46***
	(0.76)	(0.47)	(0.10)	(0.10)
Amenity6	3.5***	1.9***	.022	-.4***
	(1.25)	(0.48)	(0.16)	(0.15)
Amenity7	.95	.84	.21*	-.27
	(1.31)	(0.74)	(0.11)	(0.20)
Constant	-.11	-5***	-.34	-.19
	(1.50)	(1.13)	(0.25)	(0.28)
Observations	1986	1052	1986	1052
R^2	0.145	0.208	0.084	0.103

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors clustered at BEA area level in parentheses; all models include a full set of controls as described in the text (*AgriShare, MiningShare, IncDist250, IncDist500, IncDist1500, %Black, %Native, %Asian, %Other, GrtLakes, PacificOcean, AtlanticOcean*, *LnMSApop* and *TotPop*).

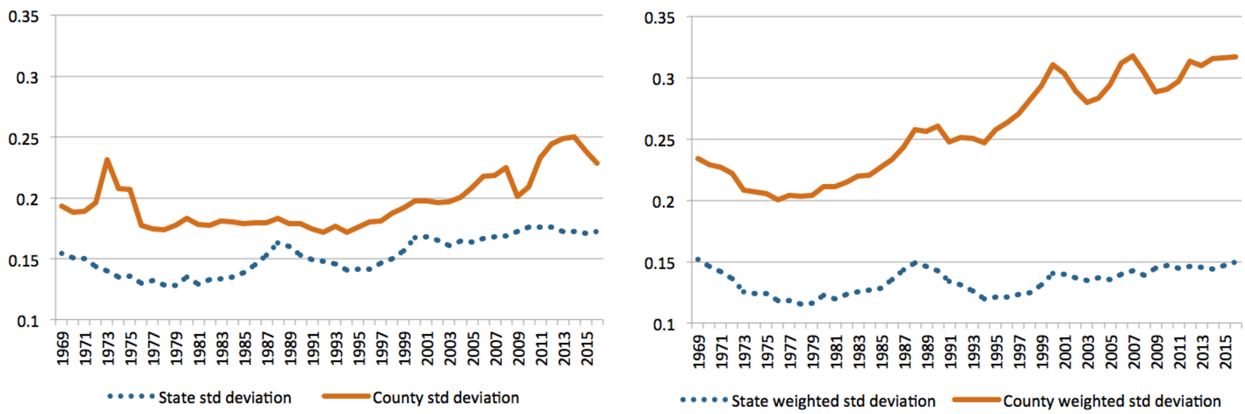

Figure 1. Average standard deviations in per-capita income (unweighted on the left, weighted on the right)

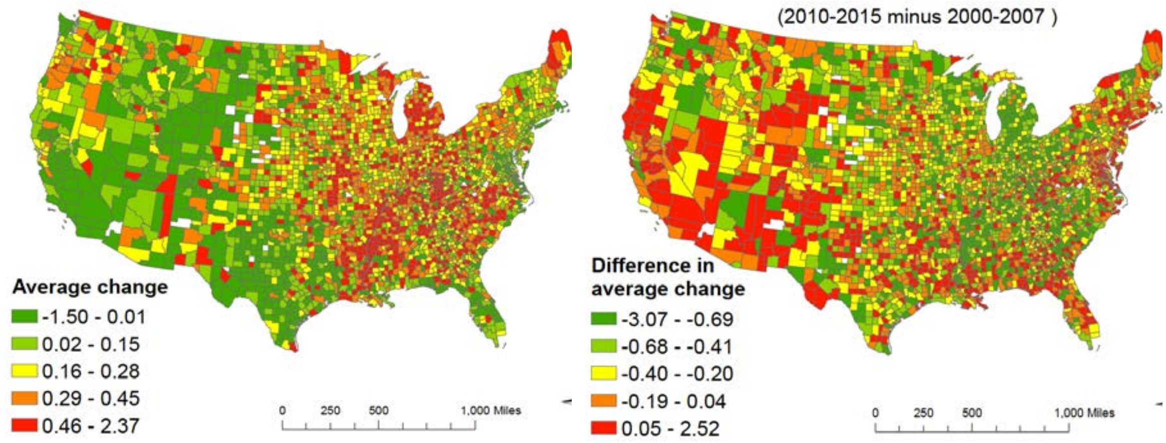

Figure 2. Pre- and Post-Recession Annual Poverty Dynamics

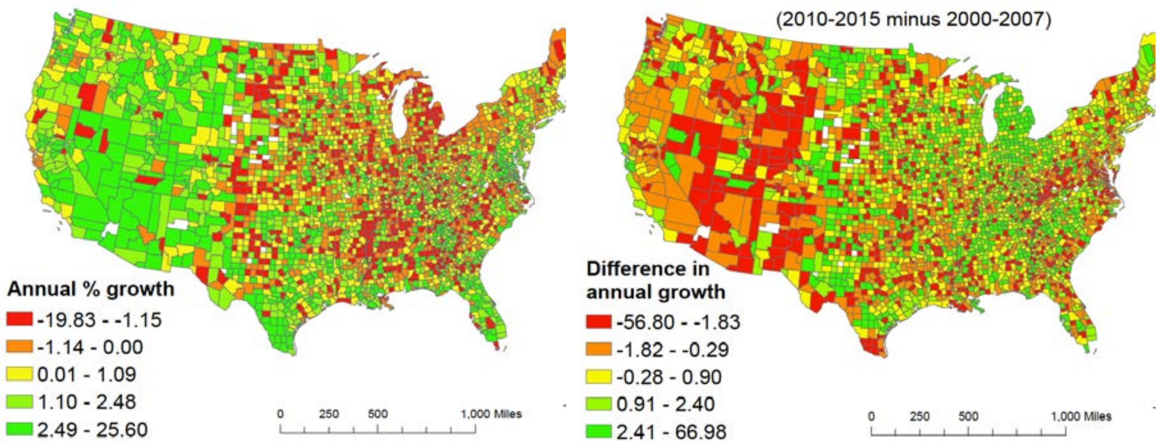

Figure 3. Pre- and post-recession employment growth dynamics

Table 1. OLS Estimation Results for Average Change in Poverty and Annualized Median Household Income Growth

Explanatory variables	Poverty rate change				Income growth	
	2010-2015		2010-2015 minus 2000-2007		2010-2015 minus 2000-2007	
	Nonmetro	Metro	Nonmetro	Metro	Nonmetro	Metro
IndMix	-.07**	-.081***	-.042**	-.093***	.11**	.28***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.05)	(0.09)
JobsFlow	-.036	6.0e-03	-.037	.028	.044	-.2
	(0.02)	(0.03)	(0.03)	(0.03)	(0.08)	(0.14)
OccEmpMobility	5.4e-03**	1.6e-03	1.9e-03	-7.4e-03***	.019***	8.4e-03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
IndEmpMobility	-1.6e-03**	4.5e-04	5.4e-04	-9.6e-04	4.2e-03**	6.4e-03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
IndDiversity	-2.7e-05	-4.7e-05*	-8.7e-06	1.1e-04	-4.6e-05	-3.8e-04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ManufShare	-.37**	-.031	-.38**	-.1	1.4**	2.4***
	(0.17)	(0.17)	(0.18)	(0.22)	(0.56)	(0.75)
LowWageManufShare	-4.1e-03	-6.6e-03*	1.2e-03	-3.3e-03	2.2e-03	-4.8e-03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
SocialCap	6.5e-03	-.016	-4.9e-03	-.02	.012	-.013
	(0.01)	(0.01)	(0.02)	(0.02)	(0.07)	(0.07)
%LessHS	-5.8e-03	-7.1e-03**	-6.8e-03*	-5.2e-03	.01	-5.3e-03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
%BA	-.012***	-7.7e-03**	-.015**	-.014**	.027	.041
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.03)
PovRate1960	2.0e-03	2.2e-03	2.6e-03	7.6e-04	-.024***	-8.6e-03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
NearMSAkm	-5.5e-04**	1.0e-03	-4.3e-04*	3.6e-03***	2.2e-03***	-4.1e-03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Amenity4	-.058**	.021	.055**	.065**	-.13	-.14
	(0.03)	(0.02)	(0.03)	(0.03)	(0.10)	(0.11)
Amenity5	-.05	.014	.2***	.059	-.78***	-.31
	(0.05)	(0.07)	(0.05)	(0.09)	(0.18)	(0.26)
Amenity6	-4.3e-03	.044	.36***	.16*	-1.3***	-.47*
	(0.07)	(0.06)	(0.05)	(0.09)	(0.22)	(0.27)
Amenity7	-6.7e-03	.1	.5***	.33***	-1.1***	-.81*
	(0.07)	(0.08)	(0.09)	(0.11)	(0.28)	(0.42)
Constant	.76**	.63**	-.026	-.15	-.39	-.41
	(0.31)	(0.28)	(0.14)	(0.14)	(0.39)	(0.56)
Observations	1986	1052	1986	1052	1986	1052
R^2	0.165	0.199	0.084	0.147	0.225	0.190

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors clustered at BEA area level in parentheses; all models include a full set of controls as described in the text (*AgriShare, MiningShare, IncDist250, IncDist500, IncDist1500, %Black, %Native, %Asian, %Other, GrtLakes, PacificOcean, AtlanticOcean, LnMSApop, TotPop* and state fixed effects in the 2010-2015 equation).

Table 2. Quantile Regression Results for Average Poverty Change, 2010-2015 Minus 2000-2007

Explanatory variables	10th percentile		90th percentile	
	Nonmetro	**Metro**	**Nonmetro**	**Metro**
IndMix	-.046*	-.038	-.012	-.043
	(0.02)	(0.05)	(0.03)	(0.03)
JobsFlow	-.018	.086	-.053	.072
	(0.04)	(0.07)	(0.05)	(0.05)
OccEmpMobility	3.9e-03	-.012**	4.7e-04	-9.3e-03***
	(0.00)	(0.01)	(0.00)	(0.00)
IndEmpMobility	1.5e-03	-2.0e-03	-3.5e-04	3.6e-04
	(0.00)	(0.00)	(0.00)	(0.00)
IndDiversity	-6.2e-06	1.0e-04	-3.4e-05	7.9e-05
	(0.00)	(0.00)	(0.00)	(0.00)
ManufShare	-.34	.066	-.78***	-.093
	(0.28)	(0.59)	(0.26)	(0.31)
LowWageManufShare	9.7e-04	-7.5e-03	1.2e-03	-4.9e-03
	(0.00)	(0.01)	(0.00)	(0.01)
SocialCap	-2.2e-03	.053	-.025	-.065**
	(0.03)	(0.06)	(0.02)	(0.03)
%LessHS	-.014***	-.016**	7.4e-03*	1.4e-03
	(0.00)	(0.01)	(0.00)	(0.00)
%BA	-8.5e-03	-.023*	-.01	-.017***
	(0.01)	(0.01)	(0.01)	(0.01)
PovRate1960	-8.6e-04	-1.3e-03	1.0e-03	1.9e-03
	(0.00)	(0.00)	(0.00)	(0.00)
NearMSAkm	-6.3e-04**	5.8e-03***	-2.6e-04	2.6e-03**
	(0.00)	(0.00)	(0.00)	(0.00)
Amenity4	.058	.13**	.067	.038
	(0.04)	(0.06)	(0.05)	(0.05)
Amenity5	.2**	-.011	.28***	.17*
	(0.08)	(0.14)	(0.07)	(0.10)
Amenity6	.32***	.26**	.42***	.15
	(0.10)	(0.10)	(0.11)	(0.11)
Amenity7	.56***	.5**	.62***	-.033
	(0.18)	(0.20)	(0.20)	(0.19)
Constant	.05	-.6**	.071	7.4e-04
	(0.17)	(0.28)	(0.18)	(0.18)
Observations	1,986	1,052	1,986	1,052
Pseudo R^2	0.123	0.142	0.104	0.150

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors clustered at BEA area level in parentheses; all models include a full set of controls as described in the text (*AgriShare, MiningShare, IncDist250, IncDist500, IncDist1500, %Black, %Native, %Asian, %Other, GrtLakes, PacificOcean, AtlanticOcean*, *LnMSApop* and *TotPop*).

Table 3. OLS Estimation Results for Annualized Employment Growth

Explanatory variables	2010-2015		2010-2015 minus 2000-2007	
	Nonmetro	Metro	Nonmetro	Metro
IndMix	.62**	.87**	.6***	1.4***
	(0.30)	(0.35)	(0.22)	(0.28)
JobsFlow	.35	.66	1.6**	1.8**
	(0.35)	(0.44)	(0.63)	(0.76)
OccEmpMobility	.092**	.18**	.099***	8.7e-03
	(0.04)	(0.07)	(0.03)	(0.05)
IndEmpMobility	.045***	-.019	.021*	.015
	(0.01)	(0.03)	(0.01)	(0.01)
IndDiversity	9.7e-05	-9.0e-06	-6.1e-04	4.0e-03
	(0.00)	(0.00)	(0.00)	(0.00)
ManufShare	3.9**	.18	1.5	-7.4
	(1.57)	(3.08)	(1.91)	(5.70)
LowWageManufShare	1.7e-03	.029	.015	9.0e-03
	(0.02)	(0.04)	(0.02)	(0.03)
SocialCap	-.34**	-.34*	.27	.14
	(0.14)	(0.20)	(0.29)	(0.23)
%LessHS	-.016	-.04	9.0e-03	.056*
	(0.03)	(0.03)	(0.03)	(0.03)
%BA	.14***	.11***	-.025	.043
	(0.04)	(0.03)	(0.05)	(0.04)
PovRate1960	-.013	.019	-.027*	-.064***
	(0.02)	(0.01)	(0.01)	(0.01)
NearMSAkm	2.8e-04	-1.7e-03	2.5e-03	-7.3e-03
	(0.00)	(0.01)	(0.00)	(0.01)
Amenity4	.31	-.023	-.31	-.072
	(0.20)	(0.21)	(0.25)	(0.35)
Amenity5	-.022	-.056	-1.5***	-.33
	(0.43)	(0.32)	(0.38)	(0.45)
Amenity6	.28	.4	-.31	-.27
	(0.65)	(0.47)	(0.89)	(0.52)
Amenity7	-1.2	.3	-1.8	.055
	(1.22)	(0.78)	(1.37)	(0.68)
Constant	-6.9**	-6	.29	-.13
	(3.10)	(10.90)	(0.99)	(1.17)
Observations	1,986	1,052	1,986	1,052
R^2	0.198	0.267	0.132	0.166

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors clustered at BEA area level in parentheses; all models include a full set of controls as described in the text (*AgriShare*, *MiningShare*, *IncDist250, IncDist500, IncDist1500, %Black, %Native, %Asian, %Other, GrtLakes, PacificOcean, AtlanticOcean, LnMSApop, TotPop* and state fixed effects in the 2010-2015 equation).

Table 4. Quantile Regression Results for Annualized Employment Growth, 2010-2015 Minus 2000-2007

Explanatory variables	**10th percentile**		**90th percentile**	
	Nonmetro	**Metro**	**Nonmetro**	**Metro**
IndMix	.11	.91***	1***	1.7***
	(0.24)	(0.29)	(0.34)	(0.31)
JobsFlow	1.2***	1.1*	.64	.43
	(0.42)	(0.62)	(0.49)	(0.58)
OccEmpMobility	.071***	.11**	.038	-.069
	(0.03)	(0.05)	(0.03)	(0.06)
IndEmpMobility	.012	.021	.029*	.029*
	(0.01)	(0.02)	(0.02)	(0.02)
IndDiversity	5.6e-04	2.6e-03	-3.3e-04	1.2e-03
	(0.00)	(0.00)	(0.00)	(0.00)
ManufShare	2.4	1.8	2.4	-3.3
	(2.44)	(2.75)	(2.74)	(2.50)
SocialCap	4.4e-03	-.018	-.026	.011
	(0.04)	(0.04)	(0.04)	(0.04)
%LessHS	-.25	-.045	.52*	.18
	(0.32)	(0.53)	(0.27)	(0.31)
%BA	-.012	.019	.051	-.014
	(0.03)	(0.04)	(0.04)	(0.04)
%Black	-.033	.015	.072	-.032
	(0.07)	(0.05)	(0.08)	(0.05)
PovRate1960	-.02	-.067***	-.028	-.033
	(0.02)	(0.02)	(0.02)	(0.02)
NearMSAkm	1.3e-03	-.017	1.9e-04	-.015*
	(0.00)	(0.01)	(0.00)	(0.01)
PacificOcean	-.35	.21	-.47	.085
	(0.38)	(0.37)	(0.36)	(0.28)
AtlanticOcean	-1	-.17	-1.5**	.33
	(0.75)	(0.60)	(0.61)	(0.50)
Amenity4	-1.4	-.86	-1.4	1.1
	(0.96)	(0.62)	(0.96)	(0.78)
Amenity5	-4.3	.72	-2.2	2*
	(3.41)	(0.78)	(3.49)	(1.06)
Amenity6	.11	.91***	1***	1.7***
	(0.24)	(0.29)	(0.34)	(0.31)
Amenity7	1.2***	1.1*	.64	.43
	(0.42)	(0.62)	(0.49)	(0.58)
Constant	-1.2	-1.1	.42	2
	(1.64)	(1.41)	(1.47)	(1.37)
Observations	1,986	1,052	1,986	1,052
Pseudo R^2	0.110	0.227	0.135	0.178

***, **, * - significant at 0.01, 0.05, and 0.1 respectively; standard errors clustered at BEA area level in parentheses; all models include a full set of controls as described in the text (*AgriShare, MiningShare, IncDist250, IncDist500, IncDist1500, %Black, %Native, %Asian, %Other, GrtLakes, PacificOcean, AtlanticOcean*, *LnMSApop* and *TotPop*).

[i]The unweighted standard deviation in market per-capita income at the county level bottomed out in 1978 at 0.20, then rose to 0.32 in 2014 before settling to 0.29 in 2016. The corresponding data for the weighted figures are bottoming out at 0.23 in 1978 and rising to just over 0.39 in 2016.

[ii]Of course, there are many ways to group economic performance determinants into broad categories (Martin et al. 2016; Martin, Sunley and Tyler 2015).

[iii] $AnnEmpGr_{c\tau} = (Emp_{ct1}/Emp_{ct})^{1/n} - 1$ and $AvPovChange_{c\tau} = (PovRate_{ct1} - PovRate_{ct})/n$, where *n* is the number of years between *t* and *t1*.

[iv]See Weinstein, Partridge and Tsvetkova. (Forthcoming) for details of the CBP data used here. It is highly correlated with *Quarterly Census of Employment and Wages* in the range of 0.95, at least for some industries, though it appears to be not quite as accurate as the data provided by the private vendor EMSI, which we use in a few cases. However, the advantage of this CBP data is that the algorithm is replicable and has undergone a peer review.

[v]For their county-level employment data, EMSI combines various publicly available sources, such as the BLS *Quarterly Census of Employment and Wages* (QCEW) and others, to fill in values suppressed due to confidentiality concerns ensuring that the final data output is consistent across counties with those reported by industry, occupation, state, and national totals. Many studies have used EMSI data (Betz et al., 2015; Tsvetkova, Partridge and Betz 2017). As noted above, the EMSI employment-by-industry data appear to be as accurate if not more accurate than the CBP data if one considers the entire year and not just March when the CBP survey takes place.

[vi]The following industries are included in the labor-intensive manufacturing category: NAICS3131 Fiber, Yarn and Thread Mills; NAICS3132 Fabric Mills; NAICS3133 Textile and Fabric Finishing and Fabric Coating Mills; NAICS3141 Textile Furnishings Mills; NAICS3149 Other Textile Product Mills; NAICS3151 Apparel Knitting Mills; NAICS3152 Cut and Sew Apparel Manufacturing; NAICS3159 Apparel Accessories and Other Apparel Manufacturing; NAICS3161 Leather and Hide Tanning and Finishing; NAICS3162 Footwear Manufacturing; NAICS3169 Other Leather and Allied Product Manufacturing; NAICS3371 Household and Institutional Furniture and Kitchen Cabinet Manufacturing;

NAICS3372 Office Furniture (including Fixtures) Manufacturing; NAICS3379 Other Furniture Related Product Manufacturing; NAICS3399 Other Miscellaneous Manufacturing.

[vii]We use EMSI data for the lagged industry shares for several reasons. First, because the “unsuppressed” CBP data are available starting in 1998, using county employment data by industry from EMSI allows us to calculate the deep lags for 1990. Second, when measuring diversity of a local economy and the relative size of manufacturing, using all industries (including government) allows characterizing the whole local economy, not just its private sector part. Given that government jobs can be a sizeable share of employment in many small counties, particularly in remote and lagging regions, variables calculated from CBP might introduce non-random measurement error. Finally, using the same data source ensures consistency in how “local economy” is defined, thus the estimation coefficients on the industry composition variables should be internally comparable.

[viii]With manufacturing share included in the model, one needs to be careful in interpreting the low-wage manufacturing share coefficient. It is picking up the *difference* between the low-wage manufacturing effect and the general manufacturing effect, not whether low-wage manufacturing has a statistically significant effect.

[ix]The social capital county-level data are available for years 1990, 1997, 2005, 2009 and 2014.