SPATIAL AWARENESS: EXAMINING THE IMPACT OF INCOME MOBILITY ON LOCAL ECONOMIC GROWTH UNDER SPATIAL AUTOCORRELATION

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ABSTRACT

This paper examines the role of inequality of opportunity on regional economic growth in the United States. We use data from the commuting zone level to estimate the relationship between intergenerational mobility, as measured by absolute and relative mobility, on per capita income growth from 2000 to 2013. We find that the geographic relationship which exists between observations in the dataset reduces the reliability of estimated coefficients and standard errors obtained using ordinary least squares estimation. We control for spatial autocorrelation caused by this geographic relationship and find that both absolute and relative mobility have a positive effect on growth, adding to the body of evidence which identifies access to opportunity as a critical determinant of economic growth. We also find that absolute and relative mobility both have a 20 percent greater marginal effect on growth than when estimated using ordinary least squares. These findings have important policy implications as they confirm the importance of the inequality of opportunity in local economic development.

Keywords: intergenerational mobility, per capita income growth, spatial econometrics

INTRODUCTION

The relationship between economic growth and inequality has been a central focus of both economic research (Banerjee & Duflo, 2003; Marrero & Rodríguez, 2013; Owen & Weil, 1998). Despite the breadth of this line of literature, there are no definitive findings, with arguments for both direct and indirect casual relationships between inequality and growth. This question has gained even more prominence as economic inequality has increased in both the developed and developing world over the late 20th and early 21st centuries. More recently, while the full economic impact of the global COVID-19 pandemic is still to be determined, it has highlighted the vast differences between groups, both within countries and around the globe. One measure of inequality that has become a larger focus in empirical studies is access to opportunity (Bradbury & Triest, 2016; Marrero & Rodríguez, 2013). This study adds to this body of literature by furthering our understanding of the importance of the access of opportunity as a determinant of economic growth. We accomplish this by estimating the impact that intergenerational income mobility has on per capita income growth in the United States. We help to identify new instrumental variables that help to control for endogeneity. We also seek to understand how the geographic relationship exhibited by observations in the dataset limits the ability to use standard linear regression frameworks.

The relationship between macroeconomic performance and inequality can be misleading, in part because most measures of income inequality often capture multiple effects that may have conflicting impacts on the macroeconomy or fail to capture the differing effects of inequality at various levels of the income distribution. Voitchovsky (2005) finds that the overall Gini coefficient, the main measurement used to capture income inequality, fails to account for the impact of inequality at different regions of the income distribution. More precisely, the positive association between inequality and growth is driven by inequality at upper portions of the income distribution, while the negative association is driven by inequality at lower levels of the income distribution. Marrero and Rodríguez (2013) argue that typical measures of inequality reflect inequality of opportunity *and* effort. Inequality of opportunity captures circumstances that a person is born into, such as socioeconomic or geographic background, for which they have no responsibility or control over. Inequality of effort on the other hand captures inequality as it relates to individual choice, such as the number of hours worked per week. They find that inequality of opportunity is negatively associated with economic growth, and inequality of effort is positively associated with growth. As such, studies which examine total inequality may find contrasting results depending upon the magnitude of these underlying effects.

Measuring inequality of opportunity is not as direct to capture as measures of overall inequality, like the Gini Coefficient or Theil Index. Marrero and Rodríguez (2013) calculate the inequality of opportunity by measuring "between-group" inequality. For example, groups are created by separating individuals based upon their father's education level or race, and then comparing the inequality between these groups. Another measurement that can capture access to opportunity is intergenerational mobility. Intergenerational mobility is a way of comparing economic outcomes between an individual and that of their parent. These outcomes are typically captured measuring educational levels for parents and children, or by comparing income levels. In many studies, an emphasis is placed on calculating the intergenerational earnings elasticity (IGE), typically found by regressing the log earnings of a parent on log earnings of their child (Solon, 1992). However, work by Chetty, Hendren, Kline and Saez (2014) has moved the focus to mobility measures based upon the parent-child relationship exhibited by their ranks in the income distribution.

To understand how intergenerational mobility relates to the inequality of opportunity, consider an economy in which the level of mobility is relatively low. Lower levels of mobility indicate the level of income persistence is high, suggesting that a person's income is highly dependent upon their parent's income. In this hypothetical economy, it is likely that access to educational institutions and other occupational networks may be dependent upon a parent's education or profession. For example, a high-income parent can afford to live in a neighborhood which has a better school district allowing their child to gain access to better colleges and higher incomes down the line, strictly based upon where they were born. In this economy, a lower level of mobility would correlate to a greater degree of inequality of opportunity. An economy with a relatively high level of mobility would have a lower persistence of earnings. In this economy, access to educational institutions and occupations are thus more likely to be based off individual's ability and talent, and there will be more equitable access to opportunity.

Despite the breakthrough on this view on inequality on growth by Marrero and Rodríguez (2013), studies which have focused on the impact of inequality of opportunity on economic growth have still had inconclusive results. Bradbury and Triest (2016) use measures of mobility that focus on income distribution rank to examine the impact on per capita income growth in the U.S. at local levels. They find measures of intergenerational mobility have varying effects on local development, with absolute measures having a strongly positive impact on growth and relative measures having a weakly positive impact on growth. Mauro (2020) uses similar measures and finds that absolute mobility has a positive impact on gross metropolitan product in the U.S. from 2000 to 2011. Aiyar and Ebeke (2020) also use intergenerational mobility as a proxy for inequality of opportunity in a cross-country growth regression. They find that omitting mobility from these regressions leads to misspecification, and that lower rates of earnings persistence lead to a greater negative effect of the Gini coefficient on growth. Ferreira, Lakner, Lugo and Özler (2018), however, find a less than conclusive result. Using two different datasets based upon income and expenditure surveys, as well as health and demographic surveys, Ferreira et al. (2018) uses a similar decomposition method to Marrero and Rodríguez (2013) to deconstruct general inequality in order to focus on opportunity. They obtain a negative association between inequality of opportunity and growth; however, this is not a significant result.

Our study contributes to this existing body of research by building on work done by Bradbury and Triest (2016) and examines the role of absolute and relative mobility on per capita income growth at the commuting zone level in the U.S. Commuting Zones are geographic aggregations of counties, not unlike metro areas, that span the entirety of the United States including rural areas (Tolbert & Sizer, 1996). We replicate key findings of Bradbury and Triest (2016) and extend upon their framework by augmenting their initial examination of endogeneity and introduce new instrumental variables for intergenerational mobility. We show that the instruments used here are valid and more effectively control for traditional endogeneity than those previously relied upon by Bradbury and Triest (2016). Our second main contribution is the addition of a spatial regression framework to test the validity of prior results to endogeneity, arising from the underlying geographic relationship exhibited by observations in the data. Correcting for spatial autocorrelation has largely been omitted from standard econometric frameworks, despite its potential impact on key findings. Spatial autocorrelation is similar to serial autocorrelation, with the exception being that persistence occurs across geographic space, rather than across time. In the case of mobility's impact on local economic growth, the existence of spatial autocorrelation is highly likely given the close proximity of observations in the data, and this can lead to inefficient and potentially biased estimators (LeSage & Pace, 2009). Given that previous studies have identified various levels of significance and magnitude with respect to the impact of mobility on growth, we show the necessity to include these controls. We implement a spatial model that accounts for the possible effect of neighboring growth rates and show that the impacts of both absolute and relative mobility are highly significant. Furthermore, we find the effect of both absolute and relative mobility on local per person income growth to be roughly 20 percent greater in magnitude than those obtained in previous studies.

DATA & METHODOLOGY

In this section, we provide an overview of the dataset used in our regression analysis and provide a description of the framework and methods used to estimate the impact of absolute and relative mobility on per capita income growth. The layout of this section will proceed in the following manner. First, we give a detailed explanation of the dataset used for our analysis. Following this, a thorough explanation of the empirical methodology used in the analysis is presented. Here, we discuss the classic linear frameworks used, along with methods used to account for spatial autocorrelation.

Data

To effectively estimate the relationship between intergenerational mobility and economic growth we obtain data from a variety of sources. The geographic area of estimation for our analysis is done at the Commuting Zone level. We adopt the commuting zone level for our analysis, following Bradbury and Triest (2016), as they offer a large array of observations for our analysis at a local level. While it is possible to obtain data at more local levels (e.g., county-level), mobility measures at this lower level of geographic aggregation are prone to be biased due to sorting and high correlation between property prices and parental income (Chetty et al., 2014).

Intergenerational income mobility is measured using two metrics developed by Chetty et al. (2014): absolute mobility and relative mobility. These measures focus on utilizing the rank of both parents and their children in each of their respective income distributions. More precisely, absolute mobility examines the expected rank in the national income distribution of children born to parents at the 25^{th} percentile of the national income distribution. Relative mobility examines the rank-rank correlation of a parent's rank in the income distribution with their child's rank in their income distribution. Unlike absolute mobility, where higher levels indicate greater mobility, high levels of relative mobility reflect a closer correlation of income rank between a parent and their child and indicate lower overall mobility. As such, we rescale relative mobility so that higher levels indicate greater mobility, as is common in the literature (Blanden, Gregg & Macmillan, 2007). Another key difference between these two measures is that absolute mobility focuses entirely on positive outcomes for families at the lower end of the income distribution. Relative mobility however can be determined by a combination of downward mobility from rich families and/or upward mobility of poor families (Chetty et al., 2014). Income mobility is measured using tax data from 2011-2012 for 30-year-old individuals (child generation) and mapped to their parents during their prime working years.

Absolute and relative mobility differ from other mainstream measures of intergenerational mobility, such as the IGE, in that they focus on the rank of the parent and their respective child in the income distribution. Measures focused on income rank have been found to be less susceptible to life-cycle bias compared to elasticity-based measures, particularly those aimed at the lower end of the income distribution like absolute mobility (Chen, Ostrovsky, & Piraino, 2017; Nybom & Stuhler, 2016, 2017). As such, they serve as better measures of inequality of opportunity and in cross-sectional growth regressions when compared against other mainstream measures of intergenerational mobility.

We also utilize several other commuting zone level measures of inequality, such as the Gini Coefficient of parental income, and the ratio of parental income at the 90th and 10^{th} percentile of the income distribution relative to the median. It is necessary to include a variety of measures beyond the Gini coefficient to control for other sources inequality in our growth regressions due to the varying impact of inequality at different levels of the income distribution (Voitchovsky, 2005). All data on income mobility and inequality was obtained from Chetty et al. (2014).

We obtain data on per capita income and population from the Bureau of Economic Analysis (BEA). Economic growth is measured as the growth in per capita income from 2000 through 2013, which coincides with the period during which individuals in the “child” generation of the mobility measures are active members of the labor force. While Bradbury and Triest (2016) also examines the period from 2007-2013, we omit this subset as there is minimal difference in their key findings. Furthermore, the 2007-2013 period may reflect cyclical changes due to the Great Recession, rather than the longer-term effects of inequality. We also include beginning of the period income per capita in our cross-sectional growth regression to allow for convergence as is typically done in the literature. As we lack access to a panel-data framework, we also include the lagged dependent to account for unmeasured commuting zone-specific factors of growth.

We control for a variety of other local characteristics such as education, age demographics and labor force participation rate that are common in growth regressions. These are gathered from the IPMUS National Historical Geographic Information System (Manson, Schroeder, Van Riper, & Kugler, 2021). Following Bradbury and Triest (2016), we control for commuting zone related exogenous factors related to their respective industry composition by including a variable estimating the pace of employment growth if each industry in the commuting zone grew at its U.S. pace. Finally, we also include measures of religious activity and other lagged demographic variables to serve as instruments. Specifically, we collect data on the number of churches per 1,000 people and the rate of religious adherents per 1,000 people (any denomination) at the county level from the 1980 and 1990 U.S. Religion Census: Religious Congregations & Membership Study conducted by the Association of Statisticians of American Religious Bodies. Lagged demographic variables from 1980 and 1990, such as proportion of foreign-born individuals, workers with a 15 minute or less commute and female headed households with children are also used as instruments following Bradbury and Triest (2016). All county level data obtained by the BEA and IPUMS NHGIS database was aggregated to the commuting zone level. A full list of variables included in our analysis, along with summary statistics, is available in Table 1.

Table 1. Summary Statistics

Variable	Mean	St. Dev.	Min	Max
Absolute Mobility	43.962	5.665	26.672	64.019
Relative Mobility	67.491	6.483	49.237	93.249
Per Capita Income, 2000	62.346	25.822	18.34	292.48
Per Capita Income Growth, 1990-2000	24.322	4.948	12.25	60.74
Per Capita Income Growth, 2000-2013	52.711	10.327	14.02	101.69
Projected Employment Growth, 2001-2013	6.561	5.158	-7.539	55.348
Less than High School Diploma/GED, 2000	0.215	0.076	0.056	0.579
More than High School Diploma/GED, 2000	0.452	0.095	0.196	0.761
Age 15 to 24, 2000	0.153	0.03	0.084	0.34
Age less than 15, 2000	0.225	0.031	0.152	0.404
Age over 54, 2000	0.255	0.05	0.112	0.437
Male Labor Force Participation, 2000	0.678	0.066	0.363	0.841
Female Labor Force Participation, 2000	0.556	0.058	0.298	0.721
Logarithm of Population, 2000	11.676	1.489	8.55	16.62
Gini of Parental Income	0.41	0.079	0.252	0.847
Parent Income Ratio 90th Percentile to 50th Percentile	2.283	0.378	1.599	3.725
Parent Income Ratio 50th Percentile to 10th Percentile	3.276	0.424	2.226	4.729
Churches per 1,000 People, 1980	2.015	0.968	0.295	6.385
Churches per 1,000 People, 1990	2.094	1.014	0.361	6.457
Religious Adherents per 1,000 People, 1980	55.533	16.097	14.468	121.511
Religious Adherents per 1,000 People, 1990	59.298	17.445	13.666	131.96

Proportion Foreign Born, 1980	0.025	0.031	0.002	0.371
Proportion Foreign Born, 1990	0.027	0.038	0.001	0.359
Workers with Commute < 15 Minutes, 1980	0.508	0.141	0.17	0.87
Workers with Commute < 15 Minutes, 1990	0.488	0.139	0.18	0.88
Households with kids headed by single mom, 1980	0.044	0.014	0.011	0.106
Households with kids headed by single mom, 1990	0.056	0.016	0.014	0.132
Observations	708			

Source: Author's calculations based upon data from the U.S. BEA, Manson et al. (2021), and Chetty et al. (2014).

Empirical Framework

We examine the relationship between our key measures of mobility, serving as a proxy for inequality of opportunity, and economic development by estimating the following empirical relationship:

$$Y = \alpha_0 + \beta X + \gamma Z + \varepsilon \tag{1}$$

Where Y is the rate of growth in per capita income, X is our measurement of intergenerational income mobility, and Z is matrix of control variables, which include the Gini of parental income, the ratio of parental income at the 90th percentile to the median, the ratio of parental income at the median to the 10th percentile, initial per capita income, lagged per capita income, projected employment growth, the proportion of individuals with less and more than a High School Diploma, the proportion of individuals between the ages of less than 15, 15 to 24, and over 54, male and female labor force participation rates and the logarithm of initial population.

One of the major hurdles concerning the validity of our results is the potential endogeneity of both absolute mobility and relative mobility in our cross-sectional growth regression. To overcome this, we turn to two stage least-squares (2SLS) estimation using two different sets of instruments. The first instrument set used comprises the rate of religious adherence per 1,000 people and the number of churches per 1,000 people in 1980 and 1990, taken from the Association of Religion Data Archives. We draw upon these religiously oriented variables to serves as suitable instruments as Chetty et al. (2014) find that areas that exhibit higher levels of absolute mobility and relative mobility also have higher rates of religious adherence. Mauro (2020) also finds that some measure of religious activity can be effectively used as an instrument for mobility in cross-sectional growth regressions. Further justification for this relationship is that religious activity may serve as an approximation of neighborhood structure and capture the presence of social networks. For example, religious institutions are more likely to play a large role in local communities where there are greater numbers of religious adherents and churches. These institutions offer various ways to aid in childhood development and will arise regardless of an area's income. At a place of worship for example, children may have to do extra studying, they have an opportunity to learn and play musical instruments, participate in plays and so on. Furthermore, many of these congregations exhibit strong social connections amongst its members and provide children with guidance from individuals in addition to their parents. These social connections may help to serve as additional role-models to keep children involved in education, away from crime and help with career paths. This additional involvement can aid low-income family in developing skills that will allow them to climb the income ladder. Although we argue that these instruments affect economic growth solely through their impact on mobility, we provide evidence of their validity and overidentification restrictions using the Sargan-Hansen's *J*-Test in our analysis. The second instrument used is composed of the 1980 and 1990 proportion foreign-born, proportion commuting less than 15 minutes, and proportion of households with children that have a female household head, following Bradbury and Triest (2016). We include the results from these instruments in our analysis to illustrate the advantage of our first instrument set.

A second potential problem that may arise by estimating the impact of mobility on growth at the commuting zone-level using standard regression frameworks is that any potential spatial effects of the observations on one another are ignored. One attempt to control for this is to estimate the model using regional fixed effects, as is typically done. However, the proximity of the observations in our analysis suggests that nearby commuting zones might have an impact on each other that are not fully captured with the broader regional fixed effects model. This point is reinforced when considering that rates of absolute mobility and relative mobility vary greatly within regions/states. Moreover, these interactions should be considered because of the potential side effects their omission may bring. Specifically, if spatial autocorrelation is ignored than the estimates obtained from standard linear models may be biased and inefficient. Also, if these effects are not controlled for then the R^2 and other goodness-of-fit statistics obtained under OLS may be overestimates (Anselin, 2001).

We control for these spatial interactions by first constructing a weighting matrix which serves to capture the spatial relationship present between observations. The matrix is constructed to give more importance to geographically nearby observations in the data and less importance to further away ones. We denote the spatial weight matrix as W. W is a $N \times N$ matrix that has zeros along its main diagonal, where N is the total number of observations in the dataset. The off-diagonal elements of W, W_{ij}, represent the spatial relationship between elements i and j. The literature points to two common methods of constructing the spatial weight matrix: nearest neighbors and some form of distance-based algorithm. Under the nearest neighbor method, W_{ij} is set equal to 1 if there are no other observations closer to either i or j and set 0 otherwise. This can be done for $k \geq 1$ nearest neighbors. Under a distance-based weighting scheme, W_{ij} is set equal to 1 if the distance between observation i and j is less than some predetermined distance L and 0 otherwise. Using either method, all rows are standardized so that they aggregate to one (Anselin, 1988; LeSage & Pace, 2009). It is important to note that the weighting matrix is taken *a priori* and must be set by the researcher. This implies that all results are conditional upon the design of the weighting matrix (Dubin, 1998). Since all potential results are conditional upon the weighting matrix, we consider multiple weighting schemes to test the sensitivity of the results as the exact spatial relationship exhibited in the data is unknown. First, a *k-nearest-neighbor* weighting structure is adopted, with $k = 3, k = 4,$ and $k = 5$ nearest neighbors. Distance-based weighting matrices are also employed, giving weight to commuting zones that are within 50 miles, 100 miles and 150 miles of each other.

In addition to the weighting matrix, the channel through which spatial feedback enters the model must also be accounted for. Generally speaking, two main models are used to control for special dependence: the spatial lag model (SAR) and the spatial error model (SEM) (Anselin, 2001). The SAR model is motivated by the existence of omitted variable bias and places the strength of the spatial interactions on the dependent variable and can be modeled as

$$y = \rho W y + X\beta + \varepsilon \tag{2}$$

where ρ is the spatial autoregressive coefficient, W is the chosen weighting matrix and ε is a vector of error terms. The SAR suffers from endogeneity and simultaneity bias through the error term, which is easily seen in its reduced form equation:

$$y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1}\varepsilon. \tag{3}$$

In the context of our analysis, the SAR is akin to modeling the economic growth of a commuting zone based upon independent variables X and the economic growth experienced by surrounding commuting zones depending upon W.

The SEM incorporates spatial dependence not through the dependent variable, but by including an additional regressor in the error structure. Formally the SEM is described as follows

$$y = X\beta + \lambda W \varepsilon + \xi \tag{4}$$

where λ is a spatial parameter, ξ is a spatially uncorrelated error term which satisfies the zero conditional mean assumption, and ε is the spatial component of the error term. The SEM is needed because of a non-spherical error term, where the structure of the spatial dependence is expressed through the off-diagonal elements of the variance-covariance matrix. Under these circumstances, OLS estimators are unbiased but are inefficient and yield inaccurate standard errors.

RESULTS

We begin by presenting the results from our initial estimation obtained from ordinary least squares. Following Anselin (2001), these OLS estimates are meant to serve as a baseline for later comparison with our findings using 2SLS, as well as our spatial results. The results of our OLS estimation can be found in Table 2. In all regressions, regional fixed effects are captured for the nine census divisions, and in models (2) and (4), we also control for various demographic variables.

The estimates for both absolute and relative mobility are strongly significant in all the regression models, indicating that there is a positive relationship between access to opportunity and economic growth. The coefficients for absolute mobility are in the range of 2.86 to 2.92 and are significant at the one percent level. The magnitude of these values indicates that a commuting zone with a level of absolute mobility one standard deviation about the average would have about 16 percent higher growth in per capita income during the sample period. The coefficients for relative mobility are in the range of 0.64 to 0.89 and are also significant at the one percent level. It is important to note that the magnitude of the effect of relative mobility on growth are smaller than those of absolute mobility. For example, a commuting zone with a level of relative mobility one standard deviation above the mean would have grown by about 4.5 percent more during the sample period.

Recall, that relative mobility captures both upward changes in income across generation *and* downward movement. This implies that, with respect to growth, upward movement at the lower levels of the income distribution is more important than relative changes throughout the income distribution. This finding is consistent with those obtained in other studies that examine the impact of mobility and inequality on growth (Bradbury & Triest, 2016; Mauro, 2020; Voitchovsky, 2005).

Turning our focus to the remaining estimated coefficients reveals some expected and some unexpected findings. The estimate for the Gini (overall inequality) is negative and significant across all columns, however, the magnitude varies drastically depending upon the measure of mobility used, as well as the regressors. However, its overall negative effect indicates that commuting zones with higher rates of overall inequality tend to grow at lower levels. Incorporating the findings of Voitchovsky (2005), we next examine the impact of inequality at various levels of the income distribution. The most significant results are found for the ratio of parent's income at the 90th percentile to the 50th percentile, which is found to be positive and significant at the one percent or five percent level. This positive sign may be surprising, given its indication that greater inequality at the top of the income distribution leads to growth, however similar findings are observed by Bradbury and Triest (2016) and are in line with Voitchovsky (2005). The coefficient for the ratio of parental income at the median to the 10th percentile is found to be positive and significant at the one percent level when controlling for absolute mobility, while negative when controlling for relative mobility.

Initial per capita income in 2000 was found to be negative and significant at the one percent level in Models (1) – (3), indicating that commuting zones being with higher levels of per capita income saw less growth during the period in question. This negative coefficient is evidence of, holding all else equal, commuting zone-level income convergence over time. We also find that lagged income growth, as measured by per capita income growth from 1990-2000, is negative and significant at the one percent level when controlling for both absolute mobility and relative mobility. Also, like previous studies, we find that predicted employment growth, based upon commuting zone-level industry composition is strongly associated with growth during the sample period. The demographic controls range with respect to their significance and sign when controlling for either absolute mobility or relative mobility.

Table 2. OLS Regression of Growth on Income Mobility

	Per Capita Income Growth, 2000-2013			
	(1)	(2)	(3)	(4)
Absolute Mobility	2.919***	2.861***		
	(0.191)	(0.199)		
Relative Mobility			0.894***	0.641***
			(0.160)	(0.155)
Gini of Parental Income	-79.018***	-29.179*	-90.004***	-45.793**
	(17.337)	(17.129)	(19.665)	(19.276)
Parent Income Ratio 90th Percentile to 50th Percentile	29.464***	22.056***	17.440***	11.101**
	(3.609)	(3.965)	(3.992)	(4.416)
Parent Income Ratio 50th Percentile to 10th Percentile	2.933	7.191***	-5.144**	-0.282
	(2.105)	(2.234)	(2.304)	(2.469)
Per Capita Income, 2000	-0.624***	-0.701***	-0.557***	-0.243
	(0.175)	(0.252)	(0.197)	(0.283)
Per Capita Income Growth, 1990-2000	-0.417***	-0.360***	-0.500***	-0.437***
	(0.074)	(0.069)	(0.083)	(0.078)
Projected Employment Growth, 2001-2013	0.752***	0.792***	0.856***	1.036***
	(0.163)	(0.163)	(0.186)	(0.183)
Less than High School Diploma/GED, 2000		20.662		75.417***
		(23.199)		(25.915)
More than High School Diploma/GED, 2000		54.988***		76.504***
		(17.847)		(20.508)
Age 15 to 24, 2000		-82.609**		-49.836

		(35.057)		(39.506)
Age less than 15, 2000		140.399***		62.722
		(36.970)		(41.279)
Age over 54, 2000		-10.654		20.296
		(35.439)		(39.952)
Male Labor Force Participation, 2000		3.864		47.234**
		(18.213)		(20.218)
Female Labor Force Participation, 2000		15.799		-36.04
		(29.452)		(33.076)
Logarithm of Population, 2000		-6.237***		-7.757***
		(0.657)		(0.730)
Constant	-81.067***	-88.855**	39.404**	36.492
	(16.364)	(37.247)	(18.309)	(42.276)
Regional Fixed Effects	Yes	Yes	Yes	Yes
Observations	708	708	708	708
R2	0.554	0.63	0.429	0.53

Source: Author's calculations based upon data from the U.S. BEA, Manson et al. (2021), and Chetty et al., 2014).
Notes: Standard errors are provided in parentheses. Significance codes: *p< 0.10; **p<0.05; ***p < 0.01.

We control for traditional endogeneity concerns by estimating the effects of absolute mobility and relative mobility on per capita income growth using 2SLS, treating absolute mobility and relative mobility as endogenous. The results of these regressions can be found in Table 3. Models (1) – (2) use religious activity to instrument for mobility, and Models (3) – (4) use lagged demographic variables following Bradbury and Triest (2016). Examining model (1)-(2) in Table 3, we find that absolute mobility is still positive and significant at the one percent level. The coefficient for absolute mobility indicates that, all else equal, a commuting zone with a level of absolute mobility one standard deviation greater than the average would have seen income per capita growth 18 percent higher during the sample period. We find a positive impact for relative mobility; however, the result is no longer statistically significant. In models (3)-(4) we find that both absolute and relative mobility are positive and significant.

The marginally different findings obtained under the two different instrument sets requires further investigation into the overall quality of the instruments. Table 4 provides the results of a series of diagnostic tests regarding the two instrument sets. With respect to the religious activity variables (Instrument Set 1), they have good strength, especially with respect to absolute mobility, with first stage F-statistics greater than 10. Furthermore, the existence of multiple instruments allows us to use Sargan-Hansen's *J*-test of overidentifying restrictions to test the validity of these instruments. For both absolute and relative mobility, we fail to reject the null hypothesis for Sargan-Hansen's *J*-Test, leading us to conclude that Instrument Set 1 is comprised of entirely valid instruments for the two mobility measures used here. When we compare these findings to the instruments used by Bradbury and Triest (2016) (Instrument Set 2), we find that while they report stronger first stage F-statistics, they are not valid as suggested by Sargan-Hansen's *J*. Considering the results of the first-stage F-statistic and Sargan-Hansen's *J*-Test, we find strong empirical evidence that our religious activity instruments are superior to Instrument Set 2, and their findings should be weighted more heavily. Building upon this point, we also conduct the Wu-Hausman Test for endogeneity to assess the consistency of the 2SLS estimators compared to those obtained using OLS. The large p-values obtained when conducting this test using Instrument Set 1 suggests that the OLS and 2SLS estimators are not inconsistent and given the superior efficiency of OLS lends evidence in support of the estimates obtained in models (2) and (4) from Table 2.

Table 3. Two-Stage Least Squares Regressions of Growth on Income Mobility

	Per Capita Income Growth, 2000-2013			
	(1)	(2)	(3)	(4)
Absolute Mobility	3.226***		1.997***	
	(0.491)		(0.368)	
Relative Mobility		1.094		0.679**
		(0.828)		(0.269)
Gini of Parental Income	-27.369	-47.504**	-33.464*	-45.936**
	(17.314)	(19.638)	(17.429)	(19.294)
Parent Income Ratio 90th Percentile to 50th Percentile	23.957***	13.878**	17.558***	11.333**
	(4.609)	(6.684)	(4.327)	(4.618)
Parent Income Ratio 50th Percentile to 10th Percentile	8.472***	1.526	4.159*	-0.131
	(2.736)	(4.091)	(2.508)	(2.621)
Per Capita Income, 2000	-0.754***	-0.216	-0.574**	-0.241
	(0.261)	(0.289)	(0.260)	(0.283)
Per Capita Income Growth, 1990-2000	-0.355***	-0.459***	-0.374***	-0.439***
	(0.069)	(0.088)	(0.070)	(0.078)
Projected Employment Growth, 2001-2013	0.750***	0.975***	0.892***	1.031***
	(0.171)	(0.214)	(0.169)	(0.185)
Constant	-113.206**	-9.688	-31.207	32.64
	(47.834)	(93.298)	(42.974)	(47.880)
Regional Fixed Effects	Yes	Yes	Yes	Yes
2000 Demographics	Yes	Yes	Yes	Yes
Observations	708	708	708	708
R2	0.628	0.524	0.620	0.530

Source: Author's calculations based upon data from the U.S. BEA, Manson et al. (2021), and Chetty et al., 2014).

Notes: Models (1) and (2) treat absolute and relative mobility as endogenous with instruments for both measures being the number of churches per 1,000 people and the total rate of religious adherent per 1,000 people in 1980 and 1990. Instruments for Models (3) and (4) are the proportion of foreign-born, proportion commuting less than fifteen minutes, and proportion of households with children that have female head and no spouse parent in 1980 and 1990 taken from Bradbury & Triest (2016). Standard errors are provided in parentheses. Significance codes: *p< 0.10; **p<0.05; ***p< 0.01.

Table 4. Two-Stage Least Squares Diagnostic Tests

		Instrument Set 1		Instrument Set 2	
Mobility Measure	Test	Statistic	P-Value	Statistic	P-value
Absolute Mobility	1st Stage F-stat	33.836	0.000	48.791	0.000
	Wu-Hausman	0.666	0.415	8.189	0.004
	Sargan-Hansen's *J*	2.473	0.480	40.378	0.000
Relative Mobility	1st Stage F-stat	12.565	0.000	56.154	0.000
	Wu-Hausman	0.313	0.576	0.029	0.864
	Sargan-Hansen's *J*	1.771	0.183	50.742	0.000

Source: Author's calculations based upon data from the U.S. BEA, Manson et al. (2021), and Chetty et al., 2014).

Notes: Instrument Set 1 is comprised of the number of churches per 1,000 people and the total rate of religious adherent per 1,000 people in 1980 and 1990. Instrument Set 2 are the proportion of foreign-born, proportion commuting less than fifteen minutes, and proportion of households with children that have female head and no spouse parent in 1980 and 1990 taken from Bradbury & Triest (2016).

Spatial Results

Given the findings from Table 3 and Table 4, endogeneity in the traditional sense does not appear to be a significant problem. This provides strong evidence of the positive effect of intergenerational mobility, especially absolute measures, on per capita income growth during the sample period. However, given the close geographic proximity of the observations to each other, the OLS model may suffer from endogeneity arising from the underlying spatial relationship. Here, our analysis further extends upon the previous work done by Bradbury and Triest (2016) and Mauro (2020) by examining this possibility. Table 5 presents the results of Moran's *I* Test for spatial autocorrelation in the OLS residuals when controlling for regional fixed effects, 2000 demographic variables and either absolute mobility or relative mobility (i.e., models (2) and (4) from Table 2). We strongly reject the null hypothesis across all weighting matrices used, suggesting that the OLS models suffer from spatial autocorrelation. Depending upon the underlying spatial structure, the estimators obtained under OLS may be inefficient and/or biased (Bivand, Pebesma & Gómex-Rubio, 2013; LeSage & Pace, 2009).

Table 5. Moran's *I* Test for Spatial Autocorrelation in OLS Residuals.

Mobility Measure = Absolute Mobility			
Weighting Matrix	Moran's *I*	E(I)	P-Value
k = 3 Nearest Neighbors	0.306	-0.019	0.000
k = 4 Nearest Neighbors	0.247	-0.018	0.000
k = 5 Nearest Neighbors	0.242	-0.018	0.000
k = 50 miles	0.361	-0.019	0.000
k = 100 miles	0.241	-0.018	0.000
k = 150 miles	0.180	-0.016	0.000
Mobility Measure = Relative Mobility			
Weighting Matrix	Moran's I	E(I)	P-Value
k = 3 Nearest Neighbors	0.416	-0.015	0.000
k = 4 Nearest Neighbors	0.374	-0.015	0.000
k = 5 Nearest Neighbors	0.373	-0.014	0.000
k = 50 miles	0.453	-0.015	0.000
k = 100 miles	0.341	-0.014	0.000
k = 150 miles	0.278	-0.013	0.000

Source: Author's calculations based upon data from the U.S. BEA, Manson et al. (2021), and Chetty et al., 2014).

We begin investigating the underlying spatial structure using LaGrange multiplier (LM) tests to identify whether the SAR or SEM best explains the spatial relationship of the data (Anselin et al., 1996). These tests examine whether the spatial parameters ρ or λ in either Equation (2) or (4) are statistically different from zero. The results of these tests are presented in Table 6. When using the standard LM tests for either the SER or SAR, we reject the null hypothesis that the spatial parameters are equal to zero. In this instance, we rely on the results from the robust versions of these tests, where we find strong evidence in favor of the SAR, which carries the implication that the OLS estimators are biased. Practically, there is also theoretical justification that the growth of smaller geographic areas would be dependent upon the growth of their close surrounding neighbors.

Table 6. LaGrange Multiplier Tests for Spatial Dependence

Mobility Measure = Absolute Mobility								
Weighting Matrix	LMerr		LMlag		RLMerr		RLMlag	
	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value
k = 3 Nearest Neighbors	123.041	0	177.489	0	0.294	0.59	54.741	0.00
k = 4 Nearest Neighbors	120.650	0	164.454	0	0.190	0.66	43.994	0.00
k = 5 Nearest Neighbors	151.698	0	203.586	0	0.788	0.37	52.676	0.00
k = 50 miles	107.735	0	130.668	0	0.820	0.37	23.753	0.00
k = 100 miles	141.479	0	185.159	0	1.551	0.21	45.231	0.00
k = 150 miles	203.063	0	217.289	0	24.502	0.00	38.727	0.00
Mobility Measure = Relative Mobility								
Weighting Matrix	LMerr		LMlag		RLMerr		RLMlag	
	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value
k = 3 Nearest Neighbors	203.880	0	256.804	0	1.138	0.29	54.062	0.00
k = 4 Nearest Neighbors	214.533	0	257.465	0	0.042	0.84	42.975	0.00
k = 5 Nearest Neighbors	264.068	0	311.876	0	0.764	0.38	48.572	0.00
k = 50 miles	144.417	0	181.244	0	1.299	0.25	38.125	0.00
k = 100 miles	222.209	0	267.242	0	0.742	0.39	45.774	0.00
k = 150 miles	305.447	0	321.534	0	22.826	0.00	38.914	0.00

Source: Author's calculations.
Notes: The above tests are the LM test for error dependence (LMerr), the LM test for a missing spatially lagged dependent variable (LMlag), the robust LM error (RLMerr), and the robust LM lag (RLMlag).

We account for the presence of a spatially lagged dependent variable and estimate an SAR for all weighting matrices. The results of these regressions, when mobility is measured using absolute mobility, are provided in Table 7. The estimated coefficient for ρ, the spatial component, is positive and significant at the one percent level across all spatial weighting matrices. This indicates that the growth rates of nearby commuting zones during the sample period have a positive effect on the growth rate of any commuting zone. We also find that the coefficient governing absolute mobility is positive and significant at the one percent level, highlighting the importance of absolute mobility in determining local economic growth. Comparing the results obtained in Table 7 to those obtained in Table 2, there is little change with the exception that the Gini coefficient is no longer statistically significant at any level. Table 8 presents the estimated SAR when controlling for intergenerational mobility using relative mobility. Again, we obtain a positive and significant spatial lagged dependent term. We also find that relative mobility is positive and is at least significant at the five percent level for all weighting matrices. We also find that when using relative mobility, the Gini is again negative, but weakly significant at the 10 percent level. Initial per capita income in 2000 is no longer significant. All models from Table 7-8 were retested for any residual spatial autocorrelation, and none was found.

Interpretation of the coefficients reported in Table 7-8 should be done cautiously. Accurate measurement for the marginal effects of key variables on growth must take into account, not only the direct effects that mobility has on growth, but additionally any potential feedback, or indirect effects, that may arise from the spatial relationship exhibited by the SAR (Bivand & Piras, 2015). This can more clearly be seen in Equation (3). We present these marginal effects for both absolute mobility and relative mobility in Table 9. The marginal effect of absolute mobility on per capita income growth is in the range of three to four percent, which is roughly 20 percent greater than the 2.86 percent impact obtained under OLS. This suggests that a commuting zone with a level of absolute mobility one standard deviation above the mean would experience about 19.5 percent per capita income growth during the sample period versus 16 percent as previously thought. The marginal effect of relative mobility on per capita income growth is in the range of 0.6 to one percent depending upon the weighting matrix used. This is on average about 20 percent higher than the 0.9 percent impact when spatial effects are ignored. In this case, a commuting zone with a level of relative mobility one standard deviation above the mean would experience five percent growth in per capita income over the sample period. Taking Tables 7 through 9 into account, the spatial relationship exhibited between commuting zones can have a large impact on the role of intergenerational mobility on local economic development.

This analysis leads to two key observations. First, absolute measures of income mobility that focus on the lower portion of the income distribution have a larger impact on per capita income growth than relative measures like relative mobility. Relative mobility however still has a positive and significant impact. Second, failure to consider the underlying spatial structure of the data can lead to a significant underestimation of the effects of both absolute *and* relative mobility on regional economic growth.

Table 7. Spatial Lag Model Results when controlling for Absolute Mobility.

	Per Capita Income Growth, 2000-2013					
	(1)	(2)	(3)	(4)	(5)	(6)
Absolute Mobility	1.908***	1.956***	1.931***	2.134***	2.032***	2.168***
	(0.186)	(0.191)	(0.191)	(0.188)	(0.190)	(0.196)
Gini of Parental Income	-19.151	-20.755	-22.718	-25.195	-20.838	-21.011
	(14.952)	(15.295)	(15.260)	(15.332)	(15.285)	(15.707)
Parent Income Ratio 90th Percentile to 50th Percentile	15.656***	16.144***	16.527***	18.215***	18.028***	18.926***
	(3.480)	(3.558)	(3.546)	(3.559)	(3.553)	(3.645)
Parent Income Ratio 50th Percentile to 10th Percentile	4.349**	4.504**	4.450**	5.131**	4.973**	5.053**
	(1.959)	(2.004)	(1.997)	(2.004)	(2.000)	(2.054)
Per Capita Income, 2000	-0.501**	-0.548**	-0.508**	-0.527**	-0.606***	-0.633***
	(0.221)	(0.226)	(0.225)	(0.226)	(0.225)	(0.231)
Per Capita Income Growth, 1990-2000	-0.284***	-0.273***	-0.281***	-0.298***	-0.283***	-0.313***
	(0.060)	(0.062)	(0.062)	(0.062)	(0.062)	(0.063)
Projected Employment Growth, 2001-2013	0.607***	0.610***	0.618***	0.622***	0.593***	0.654***
	(0.143)	(0.147)	(0.146)	(0.147)	(0.147)	(0.150)
Constant	-35.186	-41.376	-38.426	-51.696	-38.256	-41.828
	(32.667)	(33.394)	(33.300)	(33.434)	(33.375)	(34.390)
ρ	0.410***	0.410***	0.410***	0.410***	0.410***	0.410***
	(0.035)	(0.037)	(0.039)	(0.029)	(0.038)	(0.048)
Regional Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
2000 Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	708	708	708	708	708	708
Log Likelihood	-2,887.88	-2,901.01	-2,898.31	-2,902.60	-2,899.79	-2,912.50
Akaike Inf. Crit.	5,827.76	5,854.02	5,848.63	5,857.20	5,851.59	5,877.01

Source: Author's calculations based upon data from the U.S. BEA, Manson et al. (2021), and Chetty et al., 2014).
Notes: Standard errors are provided in parentheses. Columns 1 – 3 use k=3, 4, & 5 nearest neighbors weighting matrices and Columns 4 – 6 use k=50-, 100-, & 150-mile distance weighting matrices. Significance codes: *p< 0.10; **p<0.05; ***p< 0.01.

Table 8. Spatial Lag Model Results when controlling for Relative Mobility.

	Per Capita Income Growth, 2000-2013					
	(1)	(2)	(3)	(4)	(5)	(6)
Relative Mobility	0.302**	0.313**	0.321**	0.419***	0.364***	0.433***
	(0.127)	(0.130)	(0.129)	(0.132)	(0.131)	(0.135)
Gini of Parental	-26.117*	-27.945*	-30.419*	-35.280**	-29.009*	-29.728*
Income	(15.699)	(16.048)	(16.002)	(16.316)	(16.160)	(16.746)
Parent Income Ratio	7.220**	7.540**	8.251**	9.661***	9.763***	10.446***
90th Percentile to 50th Percentile	(3.598)	(3.677)	(3.666)	(3.738)	(3.702)	(3.834)
Parent Income Ratio	-1.015	-0.967	-0.897	-0.548	-0.518	-0.733
50th Percentile to 10th Percentile	(2.011)	(2.055)	(2.049)	(2.090)	(2.069)	(2.144)
Per Capita Income,	-0.189	-0.237	-0.19	-0.171	-0.294	-0.3
2000	(0.230)	(0.235)	(0.235)	(0.239)	(0.237)	(0.245)
Per Capita Income	-0.307***	-0.291***	-0.301***	-0.332***	-0.310***	-0.350***
Growth, 1990-2000	(0.064)	(0.066)	(0.066)	(0.066)	(0.066)	(0.069)
Projected Employment	0.714***	0.711***	0.719***	0.743***	0.701***	0.777***
Growth, 2001-2013	(0.150)	(0.153)	(0.153)	(0.156)	(0.155)	(0.160)
Constant	58.860*	53.446	54.407	44.802	58.851*	58.891
	(34.439)	(35.209)	(35.128)	(35.798)	(35.434)	(36.713)
ρ	0.511***	0.535***	0.561***	0.387***	0.569***	0.606***
	(0.032)	(0.034)	(0.035)	(0.028)	(0.035)	(0.042)
Regional Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
2000 Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	708	708	708	708	708	708
Log Likelihood	-2,934.21	-2,946.88	-2,942.89	-2,957.25	-2,949.81	-2,965.41
Akaike Inf. Crit.	5,920.41	5,945.76	5,937.79	5,966.51	5,951.62	5,982.83

Source: Author's calculations based upon data from the U.S. BEA, Manson et al. (2021), and Chetty et al., 2014).
Notes: Standard errors are provided in parentheses. Columns 1 – 3 use k=3, 4, & 5 nearest neighbors weighting matrices and Columns 4 – 6 use k=50-, 100-, & 150-mile distance weighting matrices. Significance codes: *p< 0.10; **p<0.05; ***p< 0.01.

Table 9. Impacts of Absolute and Relative Mobility from Spatial Lag Model Estimation

Mobility Measure = Absolute Mobility			
Weighting Matrix	Direct	Indirect	Total
k = 3 Nearest Neighbors	2.011	1.223	3.234
k = 4 Nearest Neighbors	2.045	1.305	3.349
k = 5 Nearest Neighbors	2.045	1.305	3.349
k = 50 miles	2.226	0.841	3.066
k = 100 miles	2.122	1.573	3.694
k = 150 miles	2.221	1.796	4.017
Mobility Measure = Relative Mobility			
Weighting Matrix	Direct	Indirect	Total
k = 3 Nearest Neighbors	0.329	0.288	0.617
k = 4 Nearest Neighbors	0.339	0.334	0.674
k = 5 Nearest Neighbors	0.346	0.384	0.730
k = 50 miles	0.450	0.234	0.684
k = 100 miles	0.393	0.451	0.844
k = 150 miles	0.454	0.643	1.098

Source: Author's calculations based upon data from the U.S. BEA, Manson et al. (2021), and Chetty et al., 2014).

DISCUSSION & CONCLUDING REMARKS

This study has presented further evidence of the impact of the inequality of opportunity on local economic growth. We use data on intergenerational mobility and other measures of inequality obtained from Chetty et al. (2014), along with data from a variety of other sources, to show the positive effect that access to opportunity, as measured by intergenerational mobility, has on per capita income growth at the commuting zone level in the US from 2000 to 2013. This relationship was shown to be robust to traditional endogeneity when the number of churches per 1,000 people and the rate of religious adherents per 1,000 people from 1980 and 1990 are used as instruments for either absolute mobility or relative mobility. The addition of these valid instruments to the literature is a major contribution of this study. Due to concerns over endogeneity, valid instruments are needed to accurately estimate the relationship between mobility and economic growth. We show that instrumental variables used in previous studies are invalid and fail to control for endogeneity, calling into question the findings of these earlier studies.

A second major contribution of this study is the inclusion of an econometric framework that controls for the underlying geographic relationship. The close proximity of the observations means that economic growth rates of nearby commuting zones are dependent on one another. The failure to account for this feedback, which standard linear regression frameworks do, means that any statistical conclusions obtained from cross-sectional growth studies may be invalid. We use the SAR model to control for the spatial relationship of nearby economic growth rates and find that the impact of absolute mobility and relative mobility on per capita income growth are *greater* than estimates obtained using OLS and 2SLS. Furthermore, both measures of mobility were found to be significant at the 1 percent level.

These findings are largely in line with those obtained by Bradbury and Triest (2016) and Mauro (2020) and suggest that absolute mobility and relative mobility may be of greater importance for local economic development. Another key consistency in the results obtained here and previous works is the relatively greater importance of absolute mobility over relative mobility. When controlling for spatial autocorrelation, the impact of absolute mobility on per capita growth from 2000 to 2013 is five to six time greater than relative mobility, depending upon the spatial weighting matrix used. One potential reason for this can be attributed to the construction of these variables. absolute mobility focuses strictly on the upward movement of children born to the parents at the 25^{th} percentile of the national income distribution. Relative mobility, however, captures upward and downward movement from one generation to another. As pointed out by Voitchovsky (2005), the effects of inequality on growth are more likely to be positive at the bottom tiers of the income distribution. The greater magnitude of absolute mobility may reflect this result. Another possible explanation can be found by drawing upon Marrero and Rodríguez (2013), who point out that equality of opportunity has a positive impact on growth. As such, it could be that absolute mobility does a better job than relative mobility at capturing access to opportunity. Since absolute mobility is focusing solely upon the economic outcomes of a specific subset of parents, more is held equal across commuting zones. Areas with higher levels of absolute mobility signifies that children in those areas obtain greater incomes, perhaps due to greater access to educational institutions or employment opportunities. Relative mobility may not capture these relationships as well because it looks at changes throughout income distribution. These changes can be attributed to several reasons, some of which may relate more strongly to the equality of effort and lead to a smaller impact on growth.

These results can have important implications for public policy. Policies aimed at reducing the inequality of opportunity can have a greater impact on regional per capita income growth than previously believed. It is also more apparent that policies which are targeted at the lower half of the income distribution may affect local economic growth at a higher magnitude than those focused on relative measures throughout the income distribution. Beyond this, there are numerous areas that require further study to enact effective policy. Access to opportunity, as measured by intergenerational mobility, is an important determinant of local economic development, however what are the determinants of opportunity and mobility? Studies such as Chetty et al. (2014) and Blankenau and Youderian (2015) highlight the importance of early education expenditures and the quality of schooling as potential determinants of intergenerational mobilty. Measures of school quality can vary from spending to instructor effeciency to peer effects and future work to indentify the which of measurement is dominant. Fershtman, Murphy and Weiss (1996) focuses on the importance of social status in invidual occupation choice. The importance of status is often not accounted for in large sections of the economic literature and most certainly impacts occupation and schooling decisions for one’s self and their children which could further impact intergenerational mobility.

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QUARTERLY REVIEW OF BUSINESS DISCIPLINES

February 2022

Volume 8
Number 4

A JOURNAL OF INTERNATIONAL ACADEMY OF BUSINESS DISCIPLINES
SPONSORED BY UNIVERSITY OF NORTH FLORIDA
ISSN 2334-0169 (print)
ISSN 2329-5163 (online)