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Abstract

Many studies have investigated the socioeconomic consequences of residential economic segregation in U.S. urban areas. These studies mainly focus on the impact of economic segregation on the poor or minorities and almost universally find that economic segregation hurts these groups in many ways. However, few studies investigate how economic segregation relates to the economic growth of an urban area as a whole. While there are papers that study this issue theoretically, empirical evidence is lacking. The motivation of this paper is to fill this gap. Using U.S. census data, this study documents a significant negative relationship between the initial levels of economic segregation in 1980 and the subsequent economic growth, indexed by metropolitan population growth, in 1980-2000 in U.S. metropolitan statistical areas (MSAs). Holding other things constant, MSAs having higher initial levels of economic segregation experienced substantially slower subsequent population growth.

Key Words: economic segregation; human capital externalities; social interactions; urban growth
JEL Codes: R11,O40,D62

1 Introduction

Economic segregation is a persistent feature of the US metropolitan landscape. Many studies have investigated the consequences of economic segregation from different perspectives. Some studies find that economic segregation has strong negative effects on the poor in their schooling, employment, and income (Cutler and Glaeser, 1997; Wilson, 1987; Kain, 1968; Mayer, 2002), leading to the persistent income inequality in U.S. urban areas

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(Durlauf, 1996). Other studies show that concentrated poverty largely increases the exposure to infectious diseases, crime, and the risk of mortality for people living in poor neighborhoods (Massey, 1995; Waitzman and Smith, 1998; Lobmayer and Wilkinson, 2002; Acevedo-Garcia et al., 2003). In brief, these studies find that economic segregation hurts people in poverty along multiple socio-economic dimensions.

All the aforementioned studies focus on the micro socioeconomic implications of economic segregation. Yet much less studies in the existing literature investigate the macro implications of economic segregation, such as how economic segregation may affect the growth of an urban economy as a whole. Several studies (Benabou, 1993, 1996a,b) provide theoretical analysis of this topic, yet empirical evidence is lacking. The motivation of this paper is to fill this gap by investigating how the initial patterns of economic segregation in U.S. MSAs are associated with their subsequent economic growth.

The main mechanism through which economic segregation may affect urban economic growth is by affecting human capital externalities. The study of such a connection is traced back to Lucas (1988). In that paper, Lucas highlights the central role of "external effects of human capital", which is interchangeable with human capital externalities, in explaining long-run endogenous economic growth and points out two important factors that determine the extent of human capital externalities. First, human capital externalities are a positive function of the average level of human capital. Second, human capital externalities operate through group interactions in groups "larger than the immediate family and smaller than the human race as a whole (p.38)."

The positive correlation between the average level of human capital and economic growth is well documented both internationally(Barro, 1991; Benhabib and Spiegel, 1994) and domestically (Simon, 1998, 2004; Glaeser et al., 1995; Glaeser and Shapiro, 2003; Shapiro, 2006). However, much less attention has been paid to the scope of externalities related to human capital. This may be because the scope of human capital externalities is not included in Lucas' endogenous growth model under an assumption of homogeneous agents. In such a setting, everyone is homogeneous and it does not matter with whom one interacts.

Tamura (1991) relaxes the homogeneous agent assumption by assuming heterogeneous agents in terms of their human capital level. The model predicts income convergence by assuming that any human capital improvements generated by high human capital agents automatically enters into the human capital production functions of low human capital agents. However, this assumption ignores the fact that the scope of human capital externalities is limited as mentioned in Lucas(1988). This is why Tamura's model does not obtain empirical support from a world where persistent poverty is common.

Generally speaking, individuals are more likely to interact with people spatially near to them than those who are spatially far from them. When low human capital agents are spatially insulated from interacting with high human capital agents, the human capital externalities operate poorly. If human capital externalities are crucial to long-run economic growth, then residential economic segregation may affect urban economic growth through influencing the operation of human capital externalities.

Benabou's (1993; 1996a; 1996b) theoretical analyses on economic segregation are in line with the above argument. He argues that economic segregation may affect urban economic growth through local and global levels of interactions between high human capital agents and low human capital agents. At the local level, economic segregation combined with school financing from property taxes produce significant disparities in school districts' resources. This severely hinders the human capital accumulation in poor neighborhoods due to the lack of good peers in school and role models in the neighborhoods. In extreme cases, residents in poor neighborhoods may give up education and drop out of labor markets, which lowers the supply of low-skilled workers. At the global level, economic segregation produces the polarization of skills. Such polarization does not allow for skill complementarity and contributes to productivity slowdown. Although agents with high human capital prefer neighborhood sorting to maximize their utilities, Benabou (1996a;

1996b) shows that, for an urban economy as a whole, neighborhood sorting by income hinders its long run economic growth.

The theoretical models predict a negative effects of economic segregation on urban economic growth. For the empirical side, however, only some early studies, such as Ledebur and Barnes (1992) and Rusk (1993), report some descriptive statistics that show a negative correlation between economic segregation and overall employment growth in the US MSAs. Yet to have a comprehensive understanding to such an important topic, a more thorough empirical investigation is necessary. This is the very contribution of this study to the literature.

To provide a comprehensive investigation of the relationship between economic segregation and urban economic growth, some empirical challenges and concerns are addressed. We first run regressions including different sets of metropolitan characteristics as controls to deal with the possible omitted variables bias, aiming to identify whether the estimated result is just a correlation or a causal relationship. Then we investigate whether dividing population simply into the poor group and the non-poor group and assuming homogeneity within each group bring in bias to our estimation or not. This part also investigate whether economic segregation between poor families and non-poor families has the same relationship to urban economic growth as economic segregation between two non-poor income groups does, say between middle income families and affluent families. After that, we study the interaction property of the estimated coefficient of economic segregation and urban economic growth based on nonlinear peer effect function. Finally, we deal with the high correlation between residential economic segregation and residential racial/ethnic segregation to remove the possible confounding effect of such a correlation on our estimations. After addressing all these challenges and concerns, we further provide some robustness checks by controlling urban housing market elasticity and by using alternative measures of economic segregation.

The remainder of the paper is organized as follows. Section 2 explains the measure of economic segregation and describes the data. Section 3 presents the empirical model to connect economic segregation to urban economic growth. Section 4 reports the empirical results. Finally, section 5 concludes.

2 Data and Measurements

2.1 Data

This study uses U.S. Census data from 1980 to 2000. Because the spatial boundaries of MSAs in the US change over time, using the original census data is problematic in generating variables to measure metropolitan economic growth between 1980 and 2000. To solve this problem, we use recalculated census data provided by GeoLytics company. This set of census data recalculate 1980 census data using 2000 census geographical boundaries. There are a total of 375 MSAs defined in the 2000 census with 48 US continental states included in our sample.[1]

2.2 Measuring Economic Segregation

To investigate how economic segregation relates to urban economic growth, we must first generate a proper measure of economic segregation. There are many indices designed to measure residential segregation. Among them, the dissimilarity index (D index) is commonly used in the existing literature (Massey and Denton, 1988; Abramson et al., 1995; Glaeser et al., 1995). The advantages of using the D index are easy calculation and comparability with other studies. One disadvantage, however, is that we must cut the population arbitrarily into two income groups and treats each group as homogeneous because the D index is a dichotomous measure. Doing this ignores the economic segregation within each population group. Right now we will first cut the total population into two groups to gener-

[1]Although census 2010 has been available, the recalculated census data using the same geographical boundaries as those of census 2010 have not been available yet.

ate a D index as a measure of economic segregation. In a later section, we will investigate whether such a simplification affects the main results of the estimation on the relationship between economic segregation and urban economic growth.

To calculate the D index, we follow US census bureau's definition to separate the population into people in poverty and people not in poverty.[2] The census data report the numbers of both groups for each census tract. We use this information to calculate D index for economic segregation. The D index thus describes the percentage of residents needing to move to obtain the same proportion of people in poverty (poverty rate) across all neighborhoods (approximated by census tracts) in a MSA. The formula for the D index is as follows:

$$D = \sum_{i=1}^{n} [\frac{t_i|p_i - P|}{2TP(1-P)}]$$

where t_i and p_i are the population and poverty rate in census tract i within a MSA; while T and P are the total population and average poverty rate in that MSA. The D index varies between 0 and 1. 0 stands for no economic segregation when all census tracts have the same poverty rate. 1 stands for absolute economic segregation when census tracts have either a 100 percent poverty rate or zero percent poverty rate. Therefore, when the D value is high, poverty will be sorted into some census tracts to form high poverty concentrated neighborhoods. Figure 1 gives an illustration of the D index.

(Figure 1 is inserted here)

The left part of the figure is Prescott, Arizona, whose poverty rate is 12.64%. Poverty is distributed quite evenly so that all census tracts have poverty rates between 10 percent and 20 percent. It thus has a very low D value at 0.061. The right part of the map is Naples-Macro Island, Florida. Its poverty rate is 13.48%, which is very close to that of Prescott; however, poverty is far less evenly distributed in Naples-Macro Island than in Prescott. Some coastal census tracts have poverty rates close to 0 percent, while some other census

[2]The poverty threshold in 1980 for a typical four-person family with two related children under 18 years old was $8351.

tracts in the upper right part have poverty rates between 40 and 70 percent. Such an uneven distribution of poverty generates a very high D value at 0.607.

2.3 Other Variables

We follow Glaeser et al. (1995) and Alesina and Ferrara (2005) by using population growth rather than growth in per capita income as a measure of regional economic growth. This is because population growth better reflects economic growth within a country than per capita income growth does given the assumption that labor is perfectly mobile within a country. Therefore, we use the log population growth between 1980 and 2000 to measure economic growth in U.S. MSAs in 1980-2000.

Beside the D index as a metropolitan characteristic, we also need to generate other metropolitan characteristics as controls for urban growth. To measure the average level of human capital in a MSA, we use the average years of schooling for the population above 25 years old as a proxy. There are five categories of education attainments in 1980 Census data: elementary (0-8 yr), high school dropouts (HS 1-3 yr), high school graduates (HS 4 yr), some college (Coll 1-3 yr), and bachelor and above (Coll 4+ yr). We use 4, 10, 12, 14, and 18 years of schooling respectively for each group in calculating the average schooling years. To measure the weather conditions of MSAs, Heating degree Days (HDD) is used. This is a quantitative index designed to reflect the demand for energy needed to heat a home. A higher HDD stands for colder winter in a MSA.[3] The definitions of the variables measuring other metropolitan characteristics are straightforward according to their variable names and are directly calculated using census data. Finally, we generate regional dummy variables based on U.S. census regions and divisions to capture the systematic differences of metropolitan population growth from 1980-2000 for MSAs in different geographic re-

[3] It is calculated by subtracting the base temperature (65 F) from the average temperature for each day, and then summing them up for the whole year. Data source:"Monthly Station Normals of Temperature, Precipitation, and Heating and Cooling Degree Days 1971 -2000" from National Climatic Data Center in Asheville, NC.

gions. There are 13 MSAs having boundaries on more than one census region. For these MSAs, we assign them to the census regions where the majority of their population located. We omitted South Atlantic as the control region. Therefore, totally we have 8 census region dummies.

2.4 Summary Statistics

To provide an overview of the data, statistical summaries of the main variables are presented in Table 1.

(Table 1 is inserted here)

(Table 2 is inserted here)

Table 2 presents the pairwise correlations among the variables. The correlation between regional dummies are omitted to save space. Statistical significances of correlation are also reported using asterisks. According to Table 2, U.S. metropolitan population growth between 1980 and 2000 is negatively correlated to the initial level of the D index with a statistical significance at the 99% level, which is consistent with the theoretical prediction mentioned in Section 1.

Table 2 shows that economic segregation is correlated with quite a few other metropolitan characteristics. The strongest correlation between economic segregation and other urban characteristics is with metropolitan population size. MSAs with larger population sizes are much more likely to have higher levels of economic segregation. This may be because that larger numbers of neighborhoods in larger MSAs make it easier for families to sort themselves into homogeneous neighborhoods by their incomes. Because larger MSAs are averagely more densely populated, significant positive correlation also exist between population density and economic segregation. Meanwhile, MSAs with higher average education levels and higher per capita income have higher levels of economic segregation. This may be because that individuals with higher education, normally also with higher incomes, demand more economic segregation. Beside these correlations, the presence of high Black population shares is related to higher levels of economic segregation. Surprisingly, unemployment rates are negatively correlated to economic segregation. Finally, MSAs in some geographic regions, such as East North Central, West South Central, and Middle Atlantic, had systematically higher levels of economic segregation than MSAs in other census regions.

The major empirical challenge of obtaining an unbiased estimation of the relationship between economic segregation and metropolitan population growth is the issue of omitted variables bias. Those variables that are significantly correlated to both economic segregation and metropolitan population growth are crucial controls in our estimations. Table 2 allows us to identify these variables and we will see how including these variables affect the estimation results in Section 4. These variables are average years of schooling, population density, unemployment rate, and some regional dummy variables.

The shrinkage of the U.S. manufacturing industry is significantly negatively correlated with metropolitan population growth between 1980 and 2000 as shown in Table 2. Most of the rust-belt cities that grew slowly or even shrank because of the decline of the U.S. manufacturing industries also had high levels of economic segregation in 1980. It is very easy to have an impression that the negative correlation between economic segregation and metropolitan population growth is because of the positive correlation between economic segregation and manufacturing industry share in U.S. MSAs. However, Table 2 reports a very weak correlation between these two variables, which lowers the possibility of omitted variable bias generated from variables related to the manufacturing industry.

3 Econometric Framework

We apply the econometric framework developed by Glaeser et al. (1995) to investigate the relationship between residential economic segregation and urban economic growth. In this setting, labor and capital are assumed to be perfectly mobile among different urban economies. Metropolitan areas are different only in the level of productivity and quality of life.

The level of productivity in a MSA will determine the wage rate in that MSA, while the quality of life in that MSA will affect the workers' utilities generated from the wage income. If the wage income in a MSA generates higher utility for its residents than wage incomes in other MSAs do, either because of high level of productivity (high wage rate) or better quality of life, workers in other MSAs will choose to migrate in. This will drive down the wage rate because of increased labor supply and cause congestion problems, which will lower the utility of the wage income in this MSA. In equilibrium, utilities generated from wage incomes should be the same across all MSAs, and workers should have no incentives to move. Such an equilibrium can be expressed in the following equation:

$$\overline{U} = \theta A_i^{\alpha} Q_i^{\beta} L_i^{\gamma} \tag{1}$$

where $\overline{U}$ is a national constant utility, A_i, Q_i, and L_i are the level of productivity, the quality of life and total employment in MSA i. For the exponents, there are $\theta > 0$, $\alpha > 0$, $\beta > 0$,and $\gamma < 0$.

Taking the log of both sides of equation (1) and generating the first difference between the time period t and $t+1$, we have

$$Log\left(\frac{\overline{U}_{t+1}}{\overline{U}_t}\right) = \alpha Log\left(\frac{A_{t+1}}{A_t}\right) + \beta Log\left(\frac{Q_{it+1}}{Q_{it}}\right) + \gamma Log\left(\frac{L_{it+1}}{L_{it}}\right). \tag{2}$$

Rewrite equation (2) to the following form

$$Log\left(\frac{L_{it+1}}{L_{it}}\right) = \lambda Log\left(\frac{A_{t+1}}{A_t}\right) + \delta Log\left(\frac{Q_{it+1}}{Q_{it}}\right) + \mu. \tag{3}$$

where $\lambda = -\frac{\alpha}{\gamma}$, $\delta = -\frac{\beta}{\gamma}$, $\mu = -\frac{1}{\gamma} Log\left(\frac{\overline{U}_{t+1}}{\overline{U}_t}\right)$, and they are all constants with $\lambda > 0$ and $\rho > 0$.

Equation (3) simply shows that the change of the equilibrium total employment in MSA

i between time period t and $t+1$ is determined by the changes of the level of productivity and the quality of life in that MSA. When there is increase in productivity or improvement in quality of life in MSA i, its equilibrium total employment will increase accordingly, which is the economic expansion in MSA i.

In this setting, the changes of the productivity and the quality of life in a MSA between time period t and $t+1$ are determined by the initial values of a set of urban characteristics, such as average education level, poverty rate, unemployment rate, economic segregation, population density, weather, and so on. We denote the initial pattern of economic segregation in MSA i as ES_{it} and put other urban characteristics into a vector as X_{it}. We have

$$log\left(\frac{A_{it+1}}{A_{it}}\right) = \eta_1 ES_{it} + \eta_2 X_{it} + \zeta_{it} \tag{4}$$

$$log\left(\frac{Q_{it+1}}{Q_{it}}\right) = \rho_1 ES_{it} + \rho_2 X_{it} + \xi_{it}. \tag{5}$$

Combining equations (3), (4) and (5) generates the econometric equation used in this paper to estimate the relationship between residential economic segregation and metropolitan population growth, which is σ_1 in the following equation.

$$log\left(\frac{L_{it+1}}{L_{it}}\right) = \sigma_1 ES_{it} + \sigma_2 X_{it} + \tau_{it}. \tag{6}$$

where $\sigma_1 = \lambda\eta_1 + \delta\rho_1$, $\sigma_2 = \lambda\eta_2 + \delta\rho_2$, and $\tau_{it} = \mu + \lambda\zeta_{it} + \delta\xi_{it}$.

4 Results

This section reports our empirical results. All regressions in this study use Ordinary Least Squares estimation. Robust standard errors are used in calculating t statistics in all the regressions to correct heteroscedasticity.

4.1 Benchmark Regressions

Table 3 displays benchmark regressions that include the urban characteristics that are commonly included in urban economic growth models. These urban characteristics are gradually added in regressions to observe how they affect the estimated coefficient of economic segregation. Regression 1 first includes only the D index as the measure of economic segregation. The estimated coefficient is negative and statistically significant with a t-value of -2.79. This result is consistent with the theoretical prediction that economic segregation is harmful to long-run urban economic growth. Regression 2 then adds average years of schooling into the model. Being consistent to the findings in the studies mentioned in Section 1, MSAs with higher initial average education levels experienced faster subsequent population growth. After controlling average education level, the estimated coefficient of the D index becomes quantitatively larger and statistically more significant. Results of regression 2 echo the statement in Lucas (1988) that both the average levels of human capital and the scope of group interactions are important to the operation of human capital externalities, which are crucial to long-run economic growth.

(Table 3 inserted here)

Column 3 further includes population density and unemployment rate which are significantly correlated with both metropolitan population growth and residential economic segregation in regression. If the estimated negative relationship between economic segregation and metropolitan population growth in regression 1 is actually because of the correlation between economic segregation and these urban characteristics, including these variables will largely change the estimated coefficient of the D index. The results of regression 3 show that MSAs with higher initial population densities in 1980 grew slower in the subsequent two decades. This is consistent to the finding in Barro and Sala-i-Martin (1996). The results also show that MSAs with higher initial unemployment rates had slower subsequent population growth. After controlling these two urban characteristics, the size and statistical significance of the estimated coefficient of the D index only changes slightly.

Regression 4 then adds in all other available urban characteristics. Some of them are highly correlated with metropolitan population growth but not with residential economic segregation, such as manufacturing employment share, poverty rate, Hispanic population share, and Heating Degree of Days. Some others are vice versa, such as log initial population, per cap income, and Black population share. Among them, initial manufacturing employment shares have a significantly negative relationship (t-value = -3.47) with subsequent metropolitan population growth, showing a strong impact of the downsize of the US manufacturing industry on US metropolitan population growth between 1980 and 2000. Regression 4 also finds that MSAs with higher initial Hispanic population shares had much faster subsequent population growth. This may be due to the high fertility rate among Hispanic women.[4] Another urban characteristic that has a significant estimated coefficient is Heating Degree of Days as a measure of weather. MSAs with colder winters grew much slower than MSAs with warmer winters. This result echoes the recent findings that the US households significantly increased their valuation of weather's contribution to quality of life in recent decades(Cragg and Kahn, 1999; Costa and Kahn, 2003). Finally, the initial poverty rate has a marginally significant positive relation to the subsequent population growth, which is a little counter-intuitive. Possible explanations are that poor people attract poor people to migrate in or that capital moves to MSAs with abundant supply of low-skill labor.

Other urban characteristics in regression 4 are not found to have significant associations to urban population growth. The populations of richer metropolitan areas are not found to have grown slower, which is consistent to the findings in Glaeser et al. (1995) and Rappaport (1999) using U.S. city level data and U.S. county level data respectively, [5] Meanwhile, population growth in 1980-2000 had no significant correlation to the initial metropolitan

[4]Kltsch (1990) reports that Hispanic fertility rate was about 40 percent higher than the rate of Non-Hispanics in 1980s.

[5]The convergence idea basically says that capital and labor should move to regions with lower wage rates.

population size, again showing no convergence trend. Finally, initial black population shares had no significant relationship to the subsequent urban population growth. After controlling all these urban characteristics, interestingly, the estimated coefficient of the D index is both quantitatively larger and statistically more significant, implying that the estimated relationship between economic segregation and urban population growth may be underestimated without including these urban characteristics.

Regression 5 further includes census region dummies to capture the unobserved systematic difference of urban characteristics between MSAs in different census regions. Similar to the findings in Glaeser et al. (1995) and Alesina and Ferrara (2005), regional dummies capture a large portion of the metropolitan population growth variations. Including these regional dummies increases the R square from 0.415 to 0.508. This implies that unobserved region-specific factors played important roles in shaping U.S. metropolitan population growth patterns. After controlling census region dummies, the coefficient of the D value drops from -0.730 in regression 4 to -0.541 with the statistical significance still at a 99% level.

The results in regressions 1 through 5 depict a strong negative relationship between initial economic segregation and subsequent urban growth. Is such a negative relationship only a correlation or a causal effect? Using the initial value of economic segregation to estimate the subsequent metropolitan population growth implies a causal effect of economic segregation on urban growth. However, one caveat of such a causal relationship is the possible reverse causality. In this case, economic segregation is an outcome of metropolitan population growth in previous time periods, but not a cause to subsequent metropolitan population growth. This could be true because population growth trends of U.S. MSAs in different time periods are highly correlated. [6] If higher rates of metropolitan population growth in the previous time periods lower the levels of economic segregation, such a negative relationship will be revealed as a negative correlation between the initial values of

[6] In our sample, the correlation between the population growth in 1980-1990 and the population growth in 1990-2000 is 0.74.

economic segregation and subsequent metropolitan population as what we have found in regressions 1-5 in Table 3. Does metropolitan population growth really alleviate economic segregation? To test this, we investigate how metropolitan population growth between 1980 and 1990 correlates to the changes of the levels of economic segregation between 1980 and 1990. The correlation coefficient is 0.053 with low statistical significance. Such a positive correlation is not difficult to understand if we refer back to Table 2. When a MSA experiences population growth, its population size increases and normally its population density and per capita income increase as well. As we pointed out in section 2.4, larger population size, higher population density and higher per capita income are all related to a higher level of economic segregation. Therefore, metropolitan population growth is very likely to increase the level of economic segregation but not to decrease it. We thus reject the hypothesis that the estimated negative relationship between the initial values of economic segregation and subsequent metropolitan population growth is driven by a reverse causal effect. If there is any effect of such a reverse causality on our estimation, it may only underestimate the coefficient of economic segregation.

After rejecting the possible reverse causality between metropolitan population growth and economic segregation, we still cannot identify the estimated relationship as a causal relationship due to the possible omitted variables bias. Such a negative correlation may be driven by some other urban characteristics that correlate with both urban population growth and economic segregation. It is commonly believed that using the first difference of variables instead of the levels of variables in regressions could effectively remove the potential omitted variable bias, providing stronger evidence for the causal relationship of interest. However, a recent study (Chiarella and Gao, 2002) points out that first difference method may generate Type I error to reject the real relationship estimated by using the levels of variables. A time series variable can be decomposed into a trend plus a cyclical component. When the trend represents the long-term dynamics and can be explained by fundamental economic factors, first difference method discards the long-term information and focuses on explaining the cyclical component, which generates systematic specification errors. First difference method does not generate Type I error only if the trend is a stochastic trend without long-term information.

To compare the regression models in levels and first difference, we generate panel data for the 375 MSAs. Each MSA has two observations with initial values of urban characteristics in 1980 and 1990 respectively, and population growth from 1980-1990 and from 1990-2000 respectively. The 1990 values of urban characteristics are generated in the same ways as 1980 values described before. 375 MSA dummies are also generated to capture MSA fixed effects. Regression 6 in Table 3 runs a model of levels on the pooled sample using the same controls as those in regression 5 plus year dummies. All the estimated coefficients in regression 6 have around half the sizes compared to those in regression 5. This is because the population growth is measured in a 10-year time period rather than a 20-year period in previous models. The signs and statistical significances of the estimated coefficients are all consistent with those in regression 5.

Regression 7 in Table 3 runs a model of first difference by controlling MSA fixed effects and year dummies. Heating degree of days is dropped due to no variation between 1980 and 1990. This model investigates how the changes of the initial values of urban characteristics explain the changes of the subsequent metropolitan population growth. The results of regression 7 are dramatically different from the results in regressions 5 and 6. Among all the urban characteristics, only initial population size and manufacturing employment share still have statistically significant estimated coefficients. Both of their estimated coefficients have flipped signs compared to those in regression 6. The results in regression 7 are difficult to explain and not consistent to the existing literature. Regression 7 discards the information on the different long-run population growth trends among MSAs, but compares the growth trends of a MSA in different time periods. However, different long-run population growth trends among MSAs are a result of the location choices of utility-maximizing workers. These location choices are made through comparing utilities in different MSAs based on their urban characteristics at the same time point. Therefore, discarding the connection between cross-sectional differences of urban population growth and urban characteristics in regression 7, based on (Chiarella and Gao, 2002), may generate Type I error. In this case, models of levels are more proper to use. We thus use model 5 as our benchmark regression and all the control variables in model 5 will be the standard controls in the following analyse.

Given no proper instrument variables available to provide exogenous changes of economic segregation in this study, the models of levels still cannot identify casual relationship without proper dealing with omitted variables bias. Altonji et al. (2005), however, provides a way to assess the degree of omitted variables bias. Applying their approach to our case, under the assumptions that the set of observed urban characteristics is chosen at random from the full set of urban characteristics that correlate with both economic segregation and urban population growth and that none of the urban characteristics dominates the distribution of economic segregation and urban population growth, the part of metropolitan population growth that is related to the observed urban characteristics has the same relationship with economic segregation as the part related to the unobserved urban characteristics. We therefore can use the former relationship as a guide to the latter relationship.

After controlling a rich set of urban characteristics and regional dummies, which raising R square from 0.026 in regression 1 to 0.506 in regression 5, the estimated coefficient of the D index does not become weaker or smaller, but increases its size slightly from 0.435 to 0.541 and has a stronger statistical significance. This means that the relationship between economic segregation and metropolitan population growth will be under-estimated without controlling the observed urban characteristics. If we agree with the above mentioned assumptions based on (Altonji et al., 2005), omitting the unobserved variables will also generate under-estimation to the estimated coefficient of the D value. This means that our estimation in regression 5 provides a lower bound of the true relationship given that some urban characteristics are omitted. Even if the omitted variables correlate with urban population growth and economic segregation reversely as the observed urban characteristics do, based on (Altonji et al., 2005), to fully cancel out the estimated negative relationship between economic segregation and urban population growth, they must have many times stronger correlation with urban population growth and economic segregation than the observed urban characteristics do, which is very unlikely.

Given all above analyse, we feel quite confident that there is a negative causal relationship between initial values of economic segregation and subsequent metropolitan population growth in U.S. MSAs between 1980 and 2000. According to regression 5, an initial D value one standard deviation higher (0.081) lowers the subsequent metropolitan population growth rate by 4.4 percent in two decades. Comparatively, increasing the initial average years of schooling by one standard deviation (0.876) is only related to a 3.9 percent higher subsequent population growth. Based on these results, if a MSA increases its average years of schooling by one standard deviation, but allows families to sort themselves into homogeneous neighborhoods by their incomes more thoroughly by one standard deviation, the positive impact of a higher average human capital level on urban population growth will be fully canceled out by the negative effect of a higher level of economic segregation.

4.2 Pair-wise Interclass Economic Segregation

As we mentioned before, using a dissimilarity index to measure economic segregation needs to divide the population into two groups and to assume homogeneity within each group. However, income is not a dichotomous but a continuous variable. For the group in poverty, it is relatively safe to assume it is homogeneous. For the group of non-poor, however, family incomes vary largely. Some families had incomes just a little above the poverty threshold, whereas some other families had incomes many times higher than the poverty threshold. When non-poor families at different income levels live geographically separate from each other, economic segregation exists among these income groups within the non-poor population group. Treating all non-poor families as homogeneous and ignoring the economic segregation among non-poor families may bias the estimation results on the relationship between economic segregation and urban economic growth. Some studies develop indices(Massey and Eggers, 1990; Jargowsky, 1996) to capture the economic segregation, not only between poor and non-poor, but within the non-poor families as well. Using census tract data from 1970 and 1980, Massey and Eggers (1990) defines four social classes based on specific income thresholds: poverty, lower-middle class, upper-middle class, and affluent. To compare interclass segregation, they compute six pair-wise indices of dissimilarity among the four social classes. They finally average these indices to come up with an aggregate measure of economic segregation.

Should we follow Massey and Eggers (1990) to generate an aggregate D index and use it to investigate the relationship between economic segregation and urban economic growth? Doing so implies an assumption that economic segregations between different income classes have the same relationship to urban economic growth. However, this assumption contradicts our intuition. According to aforementioned theories, economic segregation affects urban economic growth mainly through hindering the human capital accumulation of low income families or unskilled workers due to a lack of good peers in school, a lack of role models in the neighborhoods, or insulation from job information. Economic segregation between non-poor income groups, say between affluent families and upper-middle class families, however, is hard to be believed to relate urban economic growth through the same mechanism as that works between poor families and non-poor families. If economic segregation does affect urban economic growth through hindering the operation of human capital externalities, we should observe different effects of economic segregation between different income groups on urban economic growth. To test this, we follow Massey and Eggers (1990) to generate 6 pair-wise D values based on four income groups. Because Census 1980 reports household incomes in intervals, we are not able to define the poor group exactly based on the poverty thresh-hold defined by census bureau, which was $8351 for a four-member family in 1980. We thus define all households with incomes below

$10,000 as the poor group, which includes four income intervals: $9,999-7,500, $7,499-5,000, $4,999-2,500, and $2,499 below. The definitions for other three non-poor income groups are arbitrary. [7] Households with incomes between $10,000 and $19,999 are put in lower-middle income group. Households with incomes between $20,000 and $34,999 are put in upper-middle income group. Finally, households with incomes at or above $35,000 constitute affluent group. Then six pairwise D indices are generated based on these group definitions.

The summary statistics of the interclass pair-wise D values are reported in Table 1. Table 1 shows that the pair-wise D values increase with the income gaps between two groups, indicating that families are more likely to live in the same neighborhood with families with small income gaps from them than with families with large income gaps from them. Table 5 reports the correlations between these pair-wise D values. All correlation coefficients are quantitatively large and statistically significant. This shows that if economic segregation between poor families and affluent families is high in a MSA, economic segregation between two similar income groups, say the poor and lower middle income group, is also high in this MSA. Therefore, economic segregation is a general metropolitan phenomenon existing among all income groups but not mainly exists between poor families and affluent families.

Table 4 reports the estimated coefficients of the relationships between pairwise D values in 1980 and metropolitan population growth between 1980 and 2000. To make the denotation simpler, we use groups 1 through 4 to stand for the low income group, lower-middle income group, upper-middle income group, and affluent group, respectively. In regressions 1-3, each model includes one pair-wise D value between one of the non-poor income groups and the poor group. All these pair-wise D values have negative estimated coefficients with statistical significances at 99% level. The most significant estimated coefficient, interestingly, is of the D value between the lower-middle income group and the

[7] The regressions unreported here show that changing the definitions of these non-poor income groups does not affect any of our major results in this section.

poor group (t-value=-3.04), but not of the D value between the affluent group and the poor group. The affluent families are believed to be able to generate the strongest positive human capital externalities because of their high human capital. But why the economic segregation between the poor families and those lower-middle income families is found to be most costly to urban economic growth? The possible explanation is that poor families interact more with lower-middle income families than with affluent families. Also important job information useful to poor families is mainly from lower-middle income families who have similar education and skill background with them but not mainly from affluent families. Therefore, living segregated from the lower-middle income group hurts the poor income group the most. Column 4 in Table 4 includes all three D values related to the poor group in one regression. The estimated coefficients are all insignificant because of the collinearity problem, indicating that no one of these pair-wise D values dominates the estimated negative relationship. We cannot reject the hypothesis that economic segregation between poor families and all other non-poor income groups all have negative impacts on the subsequent metropolitan population growth.

Each regression of columns 5-7 in Table 5 then includes the pair-wise D value between each pair of non-poor income groups. All the estimated coefficients of D values are not statistically significant at above a 95% confidence level. Regression 8 includes the D value between the poor and the lower middle income and all three D values between non-poor income groups. The estimated coefficient of the D value between the poor group and the lower middle income group is still significant at a 99% confidence level, whereas the estimated coefficients of all three pair-wise D values between non-poor income groups drops sharply both quantitatively and statistically. These results are consistent with Benabou's human capital externalities model that economic segregation hurts urban economic growth through hurting low-skilled workers. The economic segregation between non-poor income groups follows similar market force of neighborhood choice, but is not significantly related to subsequent urban growth. All these findings also prove the legitimacy of our using the simple D index to investigate the relationship between residential economic segregation and metropolitan population growth in Section 4.1.

4.3 Economic Segregation and Nonlinear Peer Effect Function

Mixing low human capital agents with high human capital agents in neighborhoods is very similar to mixing low IQ students with high IQ students in classrooms. Henderson et al. (1978) found compelling evidence that peer effects were nonlinear. Student performance rose with the average classroom IQ score. The increase, however, slowed as the mean IQ rose. It suggests that when most students have high IQ, the benefits of mixing drop. Returning to the scenario of economic segregation in urban area, similar nonlinear neighborhood effects imply that if most of the residents in a MSA are high human capital/high income agents, the benefit of residential integration is low, or the cost of economic segregation is low. But if a large proportion of residents in a MSA are low human capital/low income agents, the cost of economic segregation will be high. If economic segregation does affect urban economic growth through affecting human capital externalities in the form of neighborhood effects, we should observe an interaction between economic segregation and the proportion of low human capital agents, approximated by poverty rate in this study, in their relationships with urban population growth. The predicted sign for the interaction term is negative. When poverty rate is higher, economic segregation is more costly thus the negative effect of economic segregation on urban population growth will be larger.

Regression 1 in Table 6 includes an interaction term between the D index and poverty rate. To make the estimated coefficient of the D index easier to interpret and to remove the possible collinearity problem, we use the demeaned D index to calculate the interaction term. The estimated coefficient of the interaction term is negative, which is consistent with the prediction; however, it is statistically insignificant. The possible explanation of the insignificant estimation is that the poverty rate is a vague representation of low human capital agents. The census bureau's definition of poverty in 1980 applied to all MSAs.

However, price levels of different MSAs varied. Without controlling price levels, poverty rates cannot measure the proportion of low income families in MSAs accurately. Instead, the unemployment rate could be a better measure of the proportion of low income families in a MSA for it is not affected by different price levels in different MSAs. Meanwhile, an important form of human capital externalities is the spreading of job information within neighborhoods. If unemployed people live geographically separated from those who are employed, such an important form of human capital externalities will be hindered. Therefore, economic segregation will be more costly when MSAs' initial unemployment rates are higher. Regression 2 includes the interaction term between the D index and the unemployment rate. The estimated coefficient is negative and is statistically significant at 95% confidence level, which is consistent to the prediction. An increase in initial unemployed rate by one standard deviation (2.3 percent) lowers the estimated coefficient of economic segregation by -0.230, which is almost half of the mean estimated coefficient of the D index (-0.483). Holding other things constant, this result shows that the negative impact of economic segregation on U.S. metropolitan population growth is much stronger in MSAs with higher initial unemployment rates.

4.4 Economic Segregation vs. Racial Segregation

This section addresses a concern of the high correlation between residential economic segregation and residential racial/ethnic segregation in U.S. metropolitan areas that may confound our estimation on the relationship between economic segregation and urban economic growth. Such a correlation exists mainly because a much larger proportion of the minority population is in poverty than that of the majority whites. Because of this, those poverty concentrated neighborhoods are very likely also concentrated with minorities and those racial/ethnic concentrated ghettos are very likely also poverty concentrated. Therefore, the observed economic segregation captures not solely the residential segregation by incomes but at least partially the residential segregation by races/ethnicities. If racial/ethnic segregation and economic segregation have different macro-economic impacts on urban growth, the estimated coefficient of economic segregation on urban growth will be biased.

To disentangle economic segregation from racial/ethnic segregation, we differentiate observed economic segregation by two types. One is economic segregation within a racial/ethnic group between its poor members and its non-poor members. Such kind of economic segregation is solely driven by family incomes but not by racial/ethnic backgrounds. It represents "pure" economic segregation. Another type is economic segregation between racial/ethnic groups when non-poor families of one racial/ethnic group live segregated from poor families of another racial/ethnic group. This type of economic segregation can be driven both by family incomes and by racial/ethnic backgrounds. Is the second type of economic segregation mainly driven by different family incomes or mainly driven by different racial/ethnic backgrounds? Do these two types of economic segregation have similar relationships with urban economic growth? How does racial/ethnic segregation relate to urban economic growth? These are some important questions we need to answer to disentangle the confundedness from racial/ethnic segregation to our estimations.

We first need to generate different indices to measure different types of economic segregation. For economic segregation within racial/ethnic groups, a simple D index is calculated for each racial/ethnic population group. There are five racial/ethnic groups defined by U.S. census: whites, blacks, Native Americans, Asian and Pacific Ocean islanders, and Hispanics. Therefore we have 5 within racial/ethnic group D values. These D values then are averaged to generate an aggregate measure, using the population share of each racial/ethnic group as its weight. We call this aggregate D value the "Within D index".

To calculate a measure of the second type of economic segregation, we make a simplification by putting all minority groups into one group. We thus have only two racial/ethnic groups: majority whites and minorities. Based on this simplification, we could generate two D values: between non-poor whites and poor minorities and between poor whites and non-poor minorities. Between these two, sociologists and economists pay much more attention to the segregation between non-poor whites and poor minorities than to the another one. We thus include this one in our analysis to represent economic segregation between racial/ethnic groups. [8] We call this D value the "Between D index". Meanwhile, to distinguish the D index we create in Section 2.2 from these new D indices, we call it "Total D index".

We also generate a measure of "pure" residential racial/ethnic segregation. When families with similar incomes, say all poor families, are sorted into different neighborhoods by races/ethnicities, such kind of residential segregation is solely driven by their racial/ethnic backgrounds but not by their family incomes. This is "pure" racial/ethnic segregation. To generate a measure of "pure" racial/ethnic segregation, we again simplify our analysis by putting all minorities into one group. Two D values may be generated to measure "pure" racial/ethnic segregation: one is between poor whites and the other is between poor minorities and between non-poor whites and non-poor minorities. We only include the D value between non-poor whites and non-poor non-whites in our study and call it as "Racial/Ethnic D Index" .[9]

(Table 7 inserted here)

The summary statistics of these D values are reported in Table 1, and the pair-wise correlations are reported in Table 7. Table 1 shows that the mean values of the Within D index, Between D index and the Racial/ethnic D index are 0.254, 0.627 and 0.494 respectively. The residential segregation between non-poor whites and poor minorities was the highest among these three types of residential segregation in U.S. metropolitan areas in 1980. Meanwhile, higher mean value for Racial/ethnic D index than the mean value of Within D index implies that families are much more likely to sort themselves into homogeneous neighborhoods by their races/ethnicities than by their incomes. Table 7 shows that

[8] In the regressions not reported here, using the other D value does not change any of our major conclusions in this section.

[9] These two D values are highly correlated with a correlation coefficient of 0.884. Including either one does not change any major results of this section.

the Racial/Ethnic D index has a much higher correlation with the Total D index (0.539) than with the Within D index (0.333). This is consistent to our statement that the Total D index as a measure of economic segregation captures a part of racial/ethnic segregation. Table 7 also shows that Between D index has a much higher correlation with Racial/Ethnic D index (0.902) than with Within D index (0.497). This implies that the residential segregation between affluent whites and poor minorities is mainly driven by their rascal/ethnic backgrounds, but not by their incomes.

(Table 8 inserted here)

In existing literature, residential segregation between affluent whites and poor minorities (measured by Between D index) attracts much more attention than residential segregation within racial/ethnic groups (measured by Within D index), say between affluent white families and poor white families. Many studies also show that poor minorities were hurt by living segregated from affluent white families.(Cutler and Glaeser, 1997) All these seem to imply that residential segregation between affluent whites and poor minorities is very important in explaining the negative relationship between economic segregation and metropolitan population growth. However, Wilson (1987) points out that it was the moving out of the middle-income black families that left the poor blacks in inner cities in a real disadvantage status. Meanwhile, Borjas (1995) finds that human capital externalities mainly operate within racial/ethnic groups because the majority of social interactions happen within racial/ethnic groups but not between them. If economic segregation affects urban economic growth through hindering the operation of human capital externalities as the theories describe, we should observe that economic segregation within racial/ethnic groups is more important in explaining the estimated negative relationship, but not economic segregation between racial/ethnic groups.

To test these predictions, regression 1 in Table 8 first includes the Within D index with the standard controls to investigate how initial pure economic segregation relates to subsequent metropolitan population growth. The estimated coefficient of the Within D value is strongly negative with a t-value of 4.04. Column 2 then includes only the Between D index and the standard controls to make a comparison. The estimated coefficient is also negative and significant at a 99% confidence level. However, in column 3, when we include Total D index, Within D index and Between D index all in the regression, only the estimated coefficient of Within D index is still significant at 99% confidence level. Both the coefficients of Total D index and Between D index become statistically insignificant. These results show that the estimated negative relationship between observed economic segregation and metropolitan population growth is dominantly driven by the "pure" economic segregation within racial/ethnic groups. These results also echo the findings in Borjas (1995) and provide positive evidence for the statement that economic segregation affects urban economic growth through hindering the operation of human capital externalities.

To answer the question whether racial/ethnic segregation has a similar relationship with urban economic growth as economic segregation has, regression 4 includes the Racial/Ethnic D index with the standard controls. The estimated coefficient of the Racial/Ethnic D index is very close to that of the Between D index in regression 2 both quantitatively and statistically. This is mainly becase of the high correlation between the Between D index and the Racial/Ethnic D index. Also similarly, after controlling Within D index in regression 5, the estimated coefficient of the Racial/Ethnic D index becomes statistically insignificant, whereas the estimated coefficient of the Within D index remains significant at a 99% confidence level. These results show that under the control of "pure" economic segregation, initial "pure" racial/ethnic segregation does not significantly associate subsequent metropolitan population growth. We cannot reject the hypothesis that "pure" racial/ethnic segregation does not systematically affect U.S. metropolitan population growth.

The results in this section further provide evidence to the robustness of the estimated negative relationship between initial levels of economic segregation and subsequent population growth in U.S. metropolitan areas. These results also point out the need for paying more attention to study the economic outcomes of residential segregation within racial/ethnic groups, especial between affluent white families and poor white families, which attracts little attention before. [10]

4.5 Robustness Checks

In the following sections, we provide some robustness checks for the estimated negative relationship between economic segregation and urban growth.

4.5.1 Housing Supply Elasticity

As we mentioned in section 2.3, it is better to use population growth to measure economic growth in cities within a country than to use per capita income growth given an assumption of free labor mobility. The free mobility assumption implies that each city has an elastic housing supply to accommodate new residents. However, as some recent studies have pointed out(Glaeser et al., 2006; Saks, 2008; Saiz, 2010), urban housing supply is very much related to the geographic conditions and government regulations on housing projects. If a city has a large portion of land undevelopable (deserts, wetlands, mountains) or is practicing tight regulations that constrain new residential real estate development, the house supply in this city will be inelastic. In this case, increases in productivity and improvements in the quality of life will not be translated into population growth which demands an increased supply of housing units, but will result in higher housing prices. Therefore, population growth may be a noise measure of U.S. metropolitan economic growth and may bias our estimation results if economic segregation in U.S. MSAs is systematically correlated to metropolitan housing supply elasticity.

To remove the possible bias of the estimation, we need to control the impact of housing supply elasticity on metropolitan population growth. We use two variables reported in Saiz

[10] The Within D index actually mainly captures the economic segregation between poor white families and non-poor white families. This is because the white families have much larger population share than other racial/ethnic groups have. The correlation between the Within D index and the D index within the whites is 0.94.

(2010) to measure housing supply elasticity. One is the Wharton Regulation Index (WRI) which measures the tightness of the regulations on residential real estate development. Another is the proportion of undevelopable land in metropolitan areas. Both of these two measures are expected to be negatively correlated to metropolitan population growth. Saiz (2010) reports these two measures in 95 metropolitan areas with population greater than 500,000 in year 2000. We find that Jersey city is in the same metropolitan area as New York city in our definition of MSAs so we drop out Jersey city. We therefore create a new sample out of our full sample including only 94 MSAs with population greater than 500,000 in year 2000. We first run the same regression as regression 5 in Table 3 using the new sample. Column 1 in Table 9 reports the estimation results. Due to small sample size, only the estimated coefficients of manufacturing employment share and unemployment rate are significant at above 95% confidence level. The coefficient of the D index is still negative, but is statistically insignificant.

To make the model parsimonious, regression 2 only includes manufacturing employment share, unemployment rate, the D index, and regional dummies. The estimated coefficient of the D index becomes significant at the 95% level. Regression 3 then adds the measures of housing supply elasticity into the model as a control. The estimated coefficient of WRI has a positive sign, which is contrary to the prediction, but it is statistically insignificant. One possible explanation is that WRI was measured in year 2000. If the tightness of the regulations on residential real estate development changed a lot between 1980 and 2000 in these MSAs, WRI in 2000 is not a good predictor of metropolitan population growth from 1980-2000. The percentage of undevelopable area, however, is found to be significantly negatively related to metropolitan population growth(t-value = -3.09). MSAs with a higher percentage of undevelopable areas experienced slower population growth in 1980-2000. After controlling housing supply elasticity, the estimated coefficient of the D index becomes quantitatively larger and statistically more significant.This result echoes our statement in section 4.1 that omitted variables may cause underestimation of the coefficient of economic segregation as dropping observable variables do. If the finding in regression 3 can be extended to MSAs with populations below 500,000, which we do not see reasons why not, our estimation of the negative relationship between economic segregation and metropolitan population growth provides the lower bound of the true relationship.

4.5.2 Neighborhood Sorting Index

Paul Jargowsky (Jargowsky, 1996; Jargowsky and Kim, 2005) points out the limitations of both the simple D index and pair-wise aggregate D index in measuring economic segregation by arguing that the cutoff points between income classes are arbitrary. He argues that collapsing a continuous income variable into limited categories discards information, and the D index is not independent of the mean and variance of the income distribution in a region. Jargowsky (1996) proposes an index called Neighborhood Sorting Index (NSI) to measure economic segregation. Although we have shown in section 4.2 that the simple D index is proper to use in this case because only the economic segregation between poor families and non-poor families is relevant to the subsequent metropolitan population growth, but we would like to use NSI to conduct a robustness check here.

The equation to generate NSI is as follows

$$NSI = \frac{\sigma_N}{\sigma_H} = \frac{\sqrt{\frac{\sum_{n=1}^{N} h_n(\bar{y}_n - \bar{y})^2}{H}}}{\sqrt{\frac{\sum_{i=1}^{H} (y_i - \bar{y})^2}{H}}} \tag{7}$$

where y_i is the income of household i, h_n is the number of households in neighborhood (approximated by census tract) n, and H and N are the total number of households and neighborhoods in a region.

U.S. census data do not report incomes for individual households, but only report the number of households in each income interval in a census tract. We use the middle point of an income interval to stand for the household incomes for all households in that income interval. For example, for all households between income interval of $5,000 - 7,500, we use \$6,250 to represent their income. Based on this approximation, we calculate the NSI for 375 MSAs using 1980 census data. Table 1 shows that the mean NSI value is higher than the mean D value. This is because NSI captures the economic segregation between some different income groups that are treated as equal by the D index.

Regression 4 in Table 9 includes NSI as the measure of economic segregation. Holding other things constant, MSAs having higher initial NSI values in 1980 grew substantially slower between 1980 and 2000. Such an negative relationship is statistically significant at a 95% level. An increase of the NSI value by one standard deviation (0.088) is related to 3.5 percent slower metropolitan population growth in two decades, which is only a little lower than a 4.4 percent slower population growth "explained" by one standard deviation increase of the D index. Therefore, using the NSI as a measure of economic segregation reports very similar results to using the D index, showing the robustness of negative relationship between economic segregation and urban growth.

4.5.3 Residential Segregation by Education Attainment

According to Mincer's 1974 log earning function, one's human capital is revealed by his/her income. We thus use neighborhood sorting by income to proxy the spatial distribution of human capital in this study. An alternative measure of the spatial distribution of human capital is the spatial distribution of education attainments. Compared to education attainments, income is a better measure of human capital because it not only captures one's education attainment, but also other important determinants of human capital, such as on-the-job training, working experience, health condition, and so on. However, one drawback of using income to proxy human capital is that it is measured at a specific time point and may fluctuate easily with some temporary events, such as unemployment, temporarily leaving the labor market, staying in school, and so on. Meanwhile, some retired seniors have lower incomes than those still employed, but their human capital levels may be similar. Therefore, the spatial distribution of education attainment provides a more stable proxy of the spatial distribution of human capital than the spatial distribution of income does, although it has its own drawbacks.

To conduct a robustness check, we generate a measure of residential segregation by education attainment using the education attainment data for people above age 25. The census data reports education attainments in five groups as mentioned in section 2.3. To be consistent with our cut of population into the poor and the non-poor, we cut population into two groups: below high school graduation and high school graduation and above. A D value is generated to measure the residential segregation between these two groups. Regression 5 in Table 9 includes the D index by education attainment as the measure of the spatial distribution of human capital. The estimated coefficient of this D index is negative and statistically significant at the 95% confidence level. MSAs in which people sorted themselves one standard deviation (0.073) more thoroughly into homogeneous neighborhoods by their education attainments in 1980 grew 3.0 percent slower in their subsequent population in 1980-2000. This result provides further evidence on the negative relationship between economic segregation and urban economic growth.

5 Conclusion

Using U.S. census data, this study finds a significant negative effects of the initial levels of economic segregation in U.S. MSAs in 1980 on their subsequent population growth in 1980-2000. This finding is consistent with the theoretical prediction based on Benabou's((Benabou, 1993, 1996a,b)) works. Although our study is not aimed to pin down the exact mechanism through which economic segregation relates to urban economic growth, the estimation results provide positive evidence to the mechanism of hindering the positive human capital externalities between low income families and higher income families.

Being consistent with other studies, this paper also finds a positive relationship between initial average human capital level and the subsequent urban growth in U.S. MSAs, showing the importance of human capital as the growth engine of urban economies. However, based on the findings in this study, such a positive relationship can be fully canceled out if high human capital/income agents live geographically segregated from low human capital/income agents. These results echo Locus's 1988 statement on the importance of both the average human capital level and the scope of social group interactions in affecting the operation of human capital externalities, which are believed to be crucial to long-run endogenous economic growth. Existing literature predominately pays attention to the importance of high average human capital in affecting long-run economic growth. Few studies have focused on the relationship between the scope of social group interactions and long-run economic growth. The main finding of this study indicates the need to pay more attention to the spatial distribution of human capital, which is closely related to the scope of social group interactions.

The findings in this study have important policy implications. The negative effects of economic segregation on urban growth implies that neighborhood sorting by income as a market outcome is not socially optimal. The demand for neighborhood sorting is too high because families, especially affluent families, ignore the social costs of economic segregation when they choose to live segregated from low income families. To bring the market outcomes back to the social optimum, local governments need to internalize the social costs of neighborhood sorting by encouraging more neighborhood integration, creating more social interactions between high human capital agents and low human capital agents. This can be done through changing zoning policy, public housing policy, and so on.

Some other findings of this study are as follows. First, only the economic segregation between poor families and non-poor families, but not the economic segregation among non-poor income groups, has a statistically significant relationship with subsequent metropolitan population growth. Second, the negative relationship between economic segregation and urban population growth is nonlinear. When the initial unemployment rates are higher, economic segregation is more costly and has stronger negative relationship with urban population growth. Third, economic segregation within racial/ethnic groups, especially between poor white families and non-poor white families, has strong negative relationship with U.S. metropolitan population growth. Economic segregation between racial/ethnic groups, typically the one between affluent majority white families and poor minority families which attracted most attention, is found to have no significant association with U.S. metropolitan population growth under the control of economic segregation within racial/ethnic groups.

References

ABRAMSON, A., M. TOBIN AND M. VANDERGOOT, "The changing geography of metropolitan opportunity: The segregation of the poor in US metropolitan areas, 1970 to 1990," *Housing Policy Debate* 6 (1995), 45–72.

ACEVEDO-GARCIA, D., K. LOCHNER, T. OSYPUK AND S. SUBRAMANIAN, "Future directions in residential segregation and health research: a multilevel approach," *American Journal of Public Health* 93 (2003), 215.

ALESINA, A. AND E. L. FERRARA, "Ethnic Diversity and Economic Performance," *Journal of Economic Literature* 43 (2005), 762–800.

ALTONJI, J., T. ELDER AND C. TABER, "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools," *Journal of Political Economy* 113 (2005), 151–184.

BARRO, R. J., "Economic growth in a cross section of countries," *The Quarterly Journal of Economics* (1991), 407–443.

BARRO, R. J. AND X. S. I MARTIN, "Convergence across states and regions," *Brookings Papers on Economic Activity: Macroeconomics* (1996), 107.

BENABOU, R., "Workings of a city: location, education, and production," *The Quarterly Journal of Economics* (1993), 619–652.

———, "Equity and efficiency in human capital investment: the local connection," *The Review of Economic Studies* 63 (1996a), 237–264.

———, "Heterogeneity, stratification, and growth: macroeconomic implications of community structure and school finance," *The American Economic Review* (1996b), 584–609.

BENHABIB, J. AND M. M. SPIEGEL, "The role of human capital in economic development evidence from aggregate cross-country data," *Journal of Monetary Economics* 34 (1994), 143–173.

BORJAS, G. J., "Ethnicity, neighborhoods, and human-capital externalities," *The American Economic Review* (1995), 365–390.

CHIARELLA, C. AND S. GAO, "Type I spurious regression in econometrics," *University of Technology, Finance and Economics Working Paper* (2002).

COSTA, D. L. AND M. E. KAHN, "The rising price of nonmarket goods," *American Economic Review* 93 (2003), 227–232.

CRAGG, M. I. AND M. E. KAHN, "Climate consumption and climate pricing from 1940 to 1990," *Regional Science and Urban Economics* 29 (1999), 519–539.

CUTLER, D. M. AND E. L. GLAESER, "Are Ghettos Good Or Bad?," *Quarterly Journal of Economics* 112 (1997), 827–872.

DURLAUF, S. N., "A theory of persistent income inequality," *Journal of Economic Growth* 1 (1996), 75–93.

GLAESER, E., J. GYOURKO AND R. SAKS, "Urban growth and housing supply," *Journal of Economic Geography* 6 (2006), 71–89.

GLAESER, E. L., J. A. SCHEINKMAN AND A. SHLEIFER, "Economic growth in a cross-section of cities," *Journal of Monetary Economics* 36 (1995), 117–143.

GLAESER, E. L. AND J. M. SHAPIRO, "Urban growth in the 1990s: Is city living back?," *Journal of Regional Science* 43 (2003), 139–165.

HENDERSON, V., P. MIESZKOWSKI AND Y. SAUVAGEAU, "Peer group effects and educational production functions," *Journal of Public Economics* 10 (1978), 97–106.

JARGOWSKY, P., "Take the money and run: economic segregation in US metropolitan areas.," *American Sociological Review* 61 (1996), 984–998.

JARGOWSKY, P. AND J. KIM, "A measure of spatial segregation: The generalized neighborhood sorting index," *University of Texas, Dallas* (2005).

KAIN, J. F., "Housing segregation, negro employment, and metropolitan decentralization," *The Quarterly Journal of Economics* 82 (1968), 175–197.

LEDEBUR, L. C. AND W. R. BARNES, "Metropolitan disparities and economic growth," *Research Report, National League of Cities, Washington* (1992).

LOBMAYER, P. AND R. WILKINSON, "Inequality, residential segregation by income, and mortality in US cities," *Journal of Epidemiology and Community Health* 56 (2002), 183.

LUCAS, R., "On the Mechanics of Economic Development," *Journal of Monetary Economics* 22 (1988), 3–42.

MASSEY, D., "Getting away with murder: Segregation and violent crime in urban America," *University of Pennsylvania Law Review* (1995), 1203–1232.

MASSEY, D. S. AND N. A. DENTON, "Dimensions of Residential Segregation, The," *Social Forces* 67 (1988), 281.

MASSEY, D. S. AND M. L. EGGERS, "The ecology of inequality: Minorities and the concentration of poverty, 1970-1980," *American Journal of Sociology* (1990), 1153–1188.

MAYER, S. E., "How economic segregation affects children's educational attainment," *Social forces* 81 (2002), 153.

MINCER, J., *Schooling, Experience, and Earnings* (New York: Columbia University Press, 1974).

RAPPAPORT, J., *Local growth empirics* (Ph.D. dissertation, Harvard University, 1999).

RUSK, D., *Cities without suburbs* (Woodrow Wilson Center Press Washington, DC, 1993).

SAIZ, A., "The geographic determinants of housing supply," *The Quarterly Journal of Economics* 125 (2010), 1253–1296.

SAKS, R., "Job creation and housing construction: Constraints on metropolitan area employment growth," *Journal of Urban Economics* 64 (2008), 178–195.

SHAPIRO, J. M., "Smart cities: quality of life, productivity, and the growth effects of human capital," *The review of economics and statistics* 88 (2006), 324–335.

SIMON, C. J., "Human Capital and Metropolitan Employment Growth," *Journal of Urban Economics* 43 (1998), 223–243.

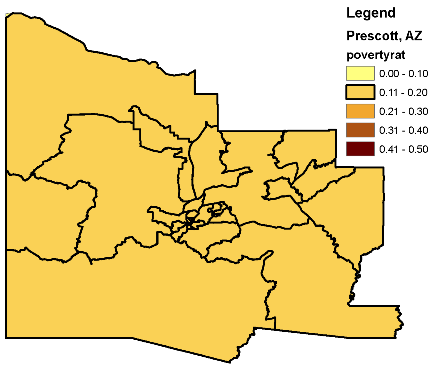
———, "Industrial reallocation across US cities, 1977-1997," *Journal of Urban Economics* 56 (2004), 119–143.

TAMURA, R., "Income Convergence in an Endogeneous Growth Model," *Journal of Political Economy* (1991), 522–540.

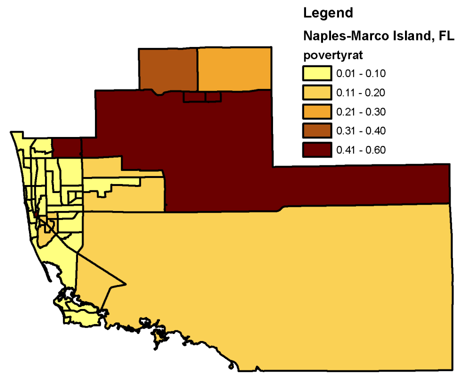
WAITZMAN, N. AND K. SMITH, "Separate but lethal: the effects of economic segregation on mortality in metropolitan America," *Milbank Quarterly* 76 (1998), 341–373.

WILSON, W. J., *The truly disadvantaged: The inner city, the underclass, and public policy* (Chicago, 1987).

Figure 1: Neighborhood Sorting of Poverty



Prescott, AZ



Naples-Macro Island, FL

Table 1: Summary Statistics

	Mean	Std. dev.	Min	Max
Population Changes				
Log Pop Growth 1980-2000	.235	.218	-.212	1.16
Control Variables in 1980				
Per Cap Income ($ 1,000)	6.988	1.047	3.979	11.514
Manufacturing employment share (%)	21.58	9.85	3.22	54.22
Average schooling years	11.531	0.876	8.229	13.989
Unemployment rate	0.068	0.023	0.019	0.149
Poverty rate	0.119	0.041	0.047	0.350
Heating degree of days (HDD)	4514	2206	0	13980
Population density (person/sq. mile)	274.1	483.1	4.0	6297.7
% non-Hispanic white	83.19	14.34	8.18	99.09
% Hispanic	5.5	11.33	0.26	91.51
% Black	9.45	10.10	0.02	44.15
(Regional Dummies)				
Pacific	0.123	0.328	0	1
Mountain	0.091	0.288	0	1
West North Central	0.083	0.276	0	1
West South Central	0.117	0.322	0	1
East North Central	0.192	0.394	0	1
East South Central	0.080	0.272	0	1
Middle Atlantic	0.096	0.295	0	1
New England	0.048	0.214	0	1
Economic Segregation Measurement				
D index (income)	0.273	0.081	0.037	0.486
Interclass D index				
1 and 2	0.161	0.046	0.025	0.274
1 and 3	0.273	0.075	0.044	0.439
1 and 4	0.393	0.097	0.062	0.595
2 and 3	0.161	0.040	0.043	0.276
2 and 4	0.307	0.076	0.052	0.477
3 and 4	0.204	0.053	0.033	0.360
Within D index	0.254	0.069	0.030	0.443
Between D index	0.627	0.166	0.098	0.968
Racial/Ethnic D index	0.494	0.165	0.046	0.801
Neighborhood Sorting Index	0.312	0.088	0.062	0.533
D index (education attainment)	0.247	0.073	0.047	0.434

Source: Author's tabulations using U.S. census data in 1980 and 2000.

Table 2: Correlation Table

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Log population growth 1980-2000	1.000											
(2)	D index (income)	-0.162**	1.000										
(3)	Average years of schooling	0.164**	0.146**	1.000									
(4)	Log initial population	-0.055	0.562**	0.164**	1.000								
(5)	Manufacturing employment share	-0.476**	0.014	-0.356**	0.086	1.000							
(6)	Per cap income ($ 1,000)	0.023	0.301**	0.582**	0.447**	-0.059	1.000						
(7)	Pop density (1000/sq mile)	-0.159**	0.354**	0.079	0.567**	0.141**	0.326**	1.000					
(8)	Unemployment rate	-0.204**	-0.174**	-0.190**	-0.181**	0.106*	-0.232**	0.000	1.000				
(9)	Poverty rate	0.184**	0.008	-0.497**	-0.201**	-0.225**	-0.699**	-0.126*	0.116*	1.000			
(10)	Hispanic population share	0.325**	0.028	-0.273**	0.053	-0.310**	-0.136**	0.027	0.011	0.422**	1.000		
(11)	Black population share	-0.055	0.346**	-0.252**	0.181**	0.050	-0.208**	0.121*	-0.034	0.475**	-0.171**	1.000	
(12)	Heating Degree of Days	-0.318**	-0.039	0.249**	-0.070	0.127*	0.149**	0.006	0.124*	-0.327**	-0.203**	-0.329**	1.000
(13)	pacific	0.248**	-0.177**	0.171**	0.047	-0.216**	0.192**	0.010	0.267**	-0.063	0.231**	-0.228**	-0.194**
(14)	Mountain	0.290**	-0.068	0.274**	-0.174**	-0.303**	-0.011	-0.141**	-0.035	-0.020	0.168**	-0.246**	0.123*
(15)	West North Central	-0.092	-0.182**	0.171**	-0.054	-0.122*	0.030	-0.098	-0.177**	-0.155**	-0.110*	-0.178**	0.258**
(16)	West South Central	0.016	0.089	-0.226**	-0.004	-0.163**	-0.129*	-0.102*	-0.279**	0.311**	0.310**	0.140**	-0.219**
(17)	East North Central	-0.352**	0.219**	0.034	0.031	0.394**	0.189**	0.090	0.279**	-0.306**	-0.160**	-0.096	0.271**
(18)	East South Central	-0.092	0.006	-0.231**	-0.044	0.107*	-0.229**	-0.065	0.097	0.266**	-0.111*	0.194**	-0.064
(19)	Middle Atlantic	-0.228**	0.113*	-0.027	0.161**	0.149**	0.011	0.245**	0.074	-0.154**	-0.083	-0.088	0.117*
(20)	New England	-0.098	0.036	0.099	0.116*	0.162**	0.055	0.165**	-0.124*	-0.149**	-0.070	-0.146**	0.167**

* $p < 0.05$, ** $p < 0.01$

Table 3: Benchmark Models

	DV: Log pop growth 1980-2000					DV: Log pop growth 1980-1990/1990-2000	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D index (income)	-0.435**	-0.510**	-0.492**	-0.730**	-0.541**	-0.185*	0.087
	(-2.79)	(-3.32)	(-2.91)	(-4.33)	(-2.97)	(-2.47)	(1.25)
Average years of schooling		0.048**	0.040**	0.061**	0.044*	0.023**	0.019
		(3.34)	(2.77)	(3.09)	(2.27)	(2.96)	(0.77)
Pop density (1000/sq mile)			-0.048*	-0.051*	-0.042	-0.024**	-0.161
			(-2.03)	(-2.43)	(-1.93)	(-2.81)	(-1.89)
Unemployment rate			-1.945**	-1.270**	-1.740**	-0.795**	-0.134
			(-4.37)	(-3.31)	(-3.70)	(-3.72)	(-0.61)
Log initial population				0.014	0.020	0.015**	-0.446**
				(0.99)	(1.44)	(2.83)	(-7.25)
Manufacturing employment share				-0.464**	-0.416**	-0.190**	0.576**
				(-3.47)	(-3.21)	(-3.05)	(4.12)
Per cap income ($ 1,000)				0.025	0.014	0.002	0.001
				(1.16)	(0.65)	(0.44)	(0.21)
Black population share				0.006	-0.150	-0.136*	-0.405
				(0.04)	(-0.85)	(-2.29)	(-1.03)
Hispanic population share				0.432**	0.404**	0.232**	-0.078
				(3.52)	(3.19)	(4.19)	(-1.27)
Poverty rate				0.969	0.808	0.337	0.256
				(1.90)	(1.53)	(1.87)	(0.97)
Heating Degree of Days				-0.025**	-0.017**	-0.008**	
				(-5.30)	(-3.28)	(-3.81)	
year=1980						0.014	-0.069*
						(0.59)	(-2.00)
Census Region dummies	NO	NO	NO	NO	YES	YES	NO
MSA dummies	NO	NO	NO	NO	NO	NO	YES
Constant	0.354**	-0.175	0.056	-0.451	-0.195	-0.163	5.796**
	(7.82)	(-1.07)	(0.33)	(-1.62)	(-0.74)	(-1.35)	(7.39)
Observations	375	375	375	375	375	750	750
R^2	0.026	0.062	0.115	0.415	0.506	0.438	0.918

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$

Table 4: Economic Segregation by Income Groups

(Dependent Variable: Log population growth 1980-2000)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average years of schooling	0.045*	0.043*	0.048*	0.047*	0.044*	0.049*	0.048*	0.047*
	(2.28)	(2.20)	(2.45)	(2.38)	(2.25)	(2.45)	(2.35)	(2.33)
Log initial population	0.018	0.019	0.018	0.020	0.008	0.010	0.010	0.020
	(1.37)	(1.43)	(1.36)	(1.51)	(0.62)	(0.81)	(0.79)	(1.43)
Manufacturing employment share	-0.413**	-0.429**	-0.392**	-0.409**	-0.401**	-0.374**	-0.364**	-0.403**
	(-3.13)	(-3.25)	(-3.01)	(-3.05)	(-3.02)	(-2.86)	(-2.76)	(-2.94)
Per cap income ($ 1,000)	0.008	0.003	0.008	0.009	0.003	0.006	0.007	0.009
	(0.35)	(0.16)	(0.35)	(0.38)	(0.14)	(0.26)	(0.30)	(0.40)
Pop density (1000/sq mile)	-0.041	-0.040	-0.040	-0.041	-0.038	-0.039	-0.039	-0.041
	(-1.83)	(-1.76)	(-1.78)	(-1.82)	(-1.65)	(-1.71)	(-1.72)	(-1.83)
Unemployment rate	-1.472**	-1.538**	-1.569**	-1.516**	-1.420**	-1.494**	-1.572**	-1.527**
	(-3.14)	(-3.28)	(-3.32)	(-3.24)	(-2.91)	(-3.09)	(-3.26)	(-3.20)
Poverty rate	0.649	0.475	0.584	0.652	0.368	0.496	0.592	0.694
	(1.22)	(0.89)	(1.11)	(1.25)	(0.69)	(0.93)	(1.14)	(1.35)
Black population share	-0.113	-0.100	-0.153	-0.101	-0.206	-0.222	-0.267	-0.124
	(-0.61)	(-0.55)	(-0.89)	(-0.55)	(-1.19)	(-1.31)	(-1.61)	(-0.67)
Hispanic population share	0.434**	0.478**	0.490**	0.465**	0.462**	0.477**	0.437**	0.443**
	(3.41)	(3.66)	(3.69)	(3.59)	(3.37)	(3.40)	(3.23)	(3.31)
Heating Degree of Days	-0.016**	-0.016**	-0.016**	-0.016**	-0.016**	-0.016**	-0.017**	-0.016**
	(-3.04)	(-3.12)	(-3.11)	(-3.04)	(-3.02)	(-3.08)	(-3.20)	(-3.13)
D index (groups 1 and 2)	-0.848**			-0.644				-0.790**
	(-3.04)			(-1.39)				(-2.64)
D index (groups 1 and 3)		-0.498**		0.014				
		(-2.70)		(0.03)				
D index (groups 1 and 4)			-0.369**	-0.160				
			(-2.78)	(-0.62)				
D index (groups 2 and 3)					-0.406			0.019
					(-1.27)			(0.04)
D index (groups 2 and 4)						-0.289		0.028
						(-1.74)		(0.06)
D index (groups 3 and 4)							-0.389	-0.192
							(-1.79)	(-0.44)
Census Region dummies	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-0.149	-0.082	-0.146	-0.179	0.002	-0.099	-0.092	-0.183
	(-0.57)	(-0.32)	(-0.57)	(-0.67)	(0.01)	(-0.39)	(-0.36)	(-0.68)
Observations	375	375	375	375	375	375	375	375
R^2	0.503	0.501	0.500	0.504	0.491	0.493	0.493	0.504

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$

Table 5: Correlation Table of Interclass Economic Segregation

	Intercalss D index	(1)	(2)	(3)	(4)	(5)	(6)
(1)	groups 1 and 2	1.000					
(2)	groups 1 and 3	0.894**	1.000				
(3)	groups 1 and 4	0.822**	0.924**	1.000			
(4)	groups 2 and 3	0.608**	0.824**	0.816**	1.000		
(5)	groups 2 and 4	0.638**	0.768**	0.922**	0.842**	1.000	
(6)	groups 3 and 4	0.567**	0.620**	0.820**	0.623**	0.903**	1.000

* $p < 0.05$, ** $p < 0.01$

Table 6: Economic Segregation and Nonlinear Peer Effect Function

(Dependent Variable: Log population growth 1980-2000)

	(1)	(2)
Average years of schooling	0.044*	0.042*
	(2.25)	(2.21)
Log initial population	0.019	0.020
	(1.39)	(1.51)
Manufacturing employment share	-0.427**	-0.378**
	(-3.23)	(-2.80)
Per cap income ($ 1,000)	0.013	0.009
	(0.61)	(0.45)
Pop density (1000/sq mile)	-0.041	-0.033
	(-1.79)	(-1.58)
Unemployment rate	-1.747**	-1.988**
	(-3.68)	(-4.16)
Poverty rate	0.777	0.800
	(1.45)	(1.53)
Black population share	-0.139	-0.125
	(-0.77)	(-0.72)
Hispanic population share	0.399**	0.402**
	(3.13)	(3.21)
Heating Degree of Days	-0.016**	-0.016**
	(-3.22)	(-3.17)
D index (income)	-0.539**	-0.531**
	(-2.97)	(-2.96)
D index * Poverty rate	-2.060	
	(-0.75)	
D index * Unemployment rate		-10.251*
		(-2.16)
Census Region dummies	YES	YES
Constant	-0.175	-0.153
	(-0.65)	(-0.59)
Observations	375	375
R^2	0.506	0.512

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$

Table 7: Correlation Table of Decomposed Residential Segregation

	D index	(1)	(2)	(3)	(4)
(1)	Total D index	1.000			
(2)	Within D index	0.801**	1.000		
(3)	Between D index	0.622**	0.497**	1.000	
(4)	Racial/Ethnic D index	0.539**	0.333**	0.902**	1.000

* $p < 0.05$, ** $p < 0.01$

Table 8: Economic Segregation vs. Racial/ethnic Segregation

(Dependent Variable: Log population growth 1980-2000)

	(1)	(2)	(3)	(4)	(5)
Average years of schooling	0.062**	0.029	0.056**	0.025	0.050*
	(2.95)	(1.56)	(2.68)	(1.26)	(2.29)
Log initial population	0.024	0.017	0.026	0.017	0.029*
	(1.87)	(1.28)	(1.93)	(1.31)	(2.21)
Manufacturing employment share	-0.375**	-0.394**	-0.373**	-0.403**	-0.391**
	(-2.95)	(-2.99)	(-2.88)	(-3.07)	(-3.05)
Per cap income ($ 1,000)	0.004	0.009	0.004	0.008	0.007
	(0.18)	(0.44)	(0.18)	(0.37)	(0.31)
Pop density (1000/sq mile)	-0.045	-0.046*	-0.048*	-0.044	-0.048*
	(-1.94)	(-2.00)	(-2.02)	(-1.95)	(-2.07)
Unemployment rate	-1.681**	-1.579**	-1.669**	-1.514**	-1.694**
	(-3.65)	(-3.32)	(-3.63)	(-3.18)	(-3.69)
Poverty rate	0.549	0.599	0.514	0.579	0.595
	(1.02)	(1.15)	(0.97)	(1.12)	(1.12)
Black population share	-0.267	-0.297	-0.310	-0.235	-0.236
	(-1.68)	(-1.84)	(-1.71)	(-1.44)	(-1.48)
Hispanic population share	0.465**	0.277*	0.405**	0.249	0.373**
	(3.57)	(2.12)	(3.08)	(1.87)	(2.78)
Heating Degree of Days	-0.016**	-0.017**	-0.016**	-0.017**	-0.016**
	(-3.22)	(-3.21)	(-3.23)	(-3.22)	(-3.30)
Within D index	-0.799**		-0.819**		-0.710**
	(-4.04)		(-2.92)		(-3.56)
Between D index		-0.217**	-0.111		
		(-2.65)	(-1.31)		
Total D index			0.156		
			(0.56)		
Racial/Ethnic D index				-0.247**	-0.148
				(-2.88)	(-1.77)
Census Region dummies	YES	YES	YES	YES	YES
Constant	-0.292	0.079	-0.210	0.121	-0.201
	(-1.12)	(0.31)	(-0.78)	(0.47)	(-0.75)
Observations	375	375	375	375	375
R^2	0.518	0.500	0.520	0.500	0.522

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$

Table 9: Robustness Checks

(Dependent Variable: Log population growth 1980-2000)

	(1)	(2)	(3)	(4)	(5)
Average years of schooling	-0.040			0.046*	0.051*
	(-0.67)			(2.32)	(2.48)
Log initial population	-0.027			0.020	0.012
	(-0.81)			(1.36)	(0.92)
Manufacturing employment share	-0.659*	-0.786**	-0.862**	-0.379**	-0.402**
	(-2.23)	(-3.35)	(-3.01)	(-2.91)	(-3.07)
Per cap income ($ 1,000)	0.011			0.014	0.002
	(0.19)			(0.65)	(0.10)
Pop density (1000/sq mile)	-0.004			-0.039	-0.043
	(-0.19)			(-1.76)	(-1.89)
Unemployment rate	-3.655**	-2.485*	-2.849**	-1.534**	-1.627**
	(-3.62)	(-2.63)	(-3.21)	(-3.25)	(-3.36)
Poverty rate	1.111			0.666	0.533
	(0.82)			(1.28)	(1.01)
Black population share	-0.373			-0.190	-0.172
	(-1.04)			(-1.08)	(-0.98)
Hispanic population share	-0.100			0.460**	0.505**
	(-0.34)			(3.39)	(3.61)
Heating Degree of Days	-0.017			-0.016**	-0.017**
	(-1.48)			(-3.13)	(-3.22)
D index (income)	-0.150	-0.632*	-0.636*		
	(-0.34)	(-2.15)	(-2.28)		
Wharton Regulation Index			0.023		
			(0.68)		
Percentage of undevelopable area			-0.002**		
			(-3.09)		
Neighborhood Sorting Index				-0.397*	
				(-2.19)	
D index (education attainment)					-0.413*
					(-2.09)
Census Region dummies	YES	YES	YES	YES	YES
Constant	1.511	0.879**	0.987**	-0.230	-0.100
	(1.92)	(7.33)	(7.67)	(-0.84)	(-0.39)
Observations	94	94	94	375	375
R^2	0.684	0.638	0.675	0.497	0.497

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$