



HARVARD Kennedy School

TAUBMAN CENTER

for State and Local Government

Urban Inequality

By

Edward L. Glaeser*

Harvard University and NBER

and

Matt Resseger and Kristina Tobio*

Harvard University

WP-2008-10

Abstract

What impact does inequality have on metropolitan areas? Crime rates are higher in places with more inequality, and people in unequal cities are more likely to say that they are unhappy. There is also a negative association between local inequality and the growth of both income and population, once we control for the initial distribution of skills. What determines the degree of inequality across metropolitan areas? Twenty years ago, metropolitan inequality was strongly associated with poverty, but today, inequality is more strongly linked to the presence of the wealthy. Inequality in skills can explain about one third of the variation in income inequality, and that skill inequality is itself explained by historical schooling patterns and immigration. There are also substantial differences in the returns to skill, related to local concentrations in different industries, and these too are strongly correlated with inequality.

* All three authors thank the Taubman Center for State and Local Government for financial support.

I. Introduction

For much of the almost 2,500 years since Plato wrote that “any city however small, is in fact divided into two, one the city of the poor, the other of the rich,” urban scholars have been struck by the remarkable amount of income inequality within dense cities (Wheeler, 2005). While there is certainly plenty of rural inequality as well, the density of cities and urban regions makes the contrast of rich and poor particularly striking. Figure 1 shows the 45 percent correlation between density and income inequality, measured with the Gini coefficient, across counties with more than one person per every two acre. The tendency of dense places to be more unequal motivates this survey of inequality in metropolitan areas, multi-county units containing a dense agglomeration of population.

America is, on the whole, relatively unequal for a developed country (Alesina and Glaeser, 2004), but there are some places within the U.S. that are a lot more equal than others. While Manhattan is the physical embodiment of big-city inequality and has a Gini coefficient of .6, the Gini coefficient of Kendall County, Illinois is only about one-half that amount. Kendall is a small but rapidly growing county on the outskirts of the Chicago area that combines agriculture with a growing presence of middle-income suburbanites. In Kendall, 9.2 percent of households earned more than 150,000 dollars in 2006, and 9.3 percent of households earned less than 25,000 dollars. In contrast, 20.4 percent of households in New York County earned more than 150,000 dollars, and 26.5 percent earned less than 25,000. In Section II of this paper, we discuss the measurement of inequality across metropolitan areas.

Just as at the national level, inequality across metropolitan areas reflects the distribution of human capital, the returns to human capital and governmental redistribution. A primary difference between local and national level inequality is that local inequality is driven to a large extent by decisions of people to live in different places. According to 2006 American Community Survey, seven percent of the U.S. population lives in a different county or country than they did only one year ago, and twenty-one percent of

the population lives in a different county or country than they did five years ago. Manhattan's inequality reflects the decisions of both rich and poor to come to the island. Since more than fourteen percent of Kendall's population lived outside the county one year ago, the area's reflects the fact it attracts homogenous people.

Paradoxically, local inequality is actually the inverse of area-level income segregation. Holding national inequality constant, local inequality falls as people are stratified across space so that rich live with rich and poor live with poor. A perfectly integrated society, where rich and poor were evenly distributed across space, would have highly unequal metropolitan areas that mirror the entire U.S. income distribution.

In Section III, we find that almost one-half of the variance in income inequality across space can be explained by differences in the skill distribution across metropolitan areas. Places with abundant college graduates and high school dropouts are areas that are particularly unequal. Traditional economic models try to explain the location of skilled and unskilled workers with differences in the returns to skill and differences in amenities (Dahl, 2002). We agree with this framework, but empirically, we find that history and immigration seem to be the most important determinants of inequality today.

Sixty percent of the heterogeneity in skills across larger metropolitan areas can be explained by the share of high school dropouts in the area in 1940 and the share of the population that is Hispanic. Long-standing historical tendencies are highly correlated with the location of high school dropouts and the location of Hispanic immigrants today. Historical skill patterns also play a huge role in the current location of college graduates (Moretti, 2004), and explain much of the distribution of skills across space.

Metropolitan inequality also reflects differences returns to skill. A modified Gini coefficient that holds the skill composition of each area constant, but allows the returns to skill to vary, can explain 50 percent of the variation in the actual Gini coefficient across metropolitan areas. The correlation between the raw Gini coefficient at the metropolitan area level and the estimated returns to a college degree in that area is 73 percent.

We do not fully understand why some places reward skill so much more strongly than others. In our data, the most powerful correlate of the returns to having a college degree is the share of population with college degrees, but that fact provides more confusion than clarity. The correlation could reflect skilled people moving to areas where there are large returns to skill. Alternatively, it might reflect human capital spillovers which cause the returns to skill to rise. Hopefully, future research will help us better understand the differences in the returns to skill across metropolitan areas.

In Section IV of this paper, we turn to the consequences of local inequality. We find a significant negative correlation between local economic growth and income inequality once we control for other initial conditions, such as the initial distribution of skills and temperature. Places with unequal skills actually grow more quickly, but places with more income inequality, holding skills constant, have slower income and population growth. Inequality is related to crime at both the national and city level (Fajnzylber, Lederman and Lloyza, 2002; Daly, Wilson and Vasdev, 2001). Our data also confirms a robust relationship between the murder rate and inequality. Luttmer (2005) documents that people are less happy when they live around richer people. We also find people who live in more unequal countries report themselves to be less happy.

In Section V, we discuss the policy issues surrounding local inequality. Even if we accept that local inequality has some unattractive consequences, the consequences of reducing local inequality, holding national inequality fixed, are quite unclear. Reducing local inequality, leaving the national skill distribution untouched, implies increased segregation of the rich and the poor.

Moreover, easy migration across areas severely limits the ability of localities to reduce income inequality through redistributive policies (Peterson, 1981). The ability to migrate means that when localities take from the rich and give to the poor, they will induce the rich to emigrate and attract more poor people, which in turn creates added burdens on the city's finances. After all, the evidence in Section III suggests that the

location of high skilled people may be quite sensitive to the returns to skill. Decreasing the returns to skill at the local level with higher taxes or other policies will surely induce some skilled workers to leave.

Our final point is that America's current schooling system puts localities at the center of any attempts to reduce national inequality through a more equal human capital distribution. While localities are inherently weak in their abilities to reduce inequality, decentralized schooling means that any attempt to equalize educational opportunities must rely heavily on localities. Not only will attempts to reduce inequality through more equal education take many years, but they will also require a tricky partnership between national and local governments.

II. Measuring Inequality Across American Metropolitan Areas

In the analysis that follows, we will use metropolitan areas as our geographic unit and the Gini coefficient as our measure of income inequality. Metropolitan areas are defined as multi-county agglomerations that surround a city with a "core urban area" of over 50,000 people. Metropolitan areas have the advantage of at least approximating local labor markets, and they are large enough to provide a certain measure of statistical precision. The disadvantage of using these areas is that they do not correspond to natural political units, which makes them awkward units for analyzing or discussing public policy.

Much of the data for this paper comes from the five-percent Integrated Public-Use Micro-Samples (IPUMS) for the 1980 and 2000 Censuses (Ruggles et al, 2008). In most cases, we will restrict ourselves to total household income, which means that we are not treating single people differently from married people. We will focus on pre-tax income inequality.¹ A particular problem with using Census data to measure income inequality is that incomes in the 2000 Census are top-coded at 999,998 dollars and at 75,000 in 1980.

¹ Our income measures, like many in this literature, exclude non-income returns from capital ownership, like the flow of services associated with owning a home.

In the case of top-coding, we use the income top-code, but recognize that this is understating the true degree of income inequality.

We use the Gini coefficient as our measure of inequality, mainly because it is the ubiquitous standard in the inequality literature. Many policy discussions of inequality focus on poverty, and reducing poverty levels is a natural topic of policy attention. Yet this essay is focused on extremes at both the upper and lower levels of the income distribution, and the Gini coefficient captures that heterogeneity. The Gini coefficient, defined as $1 - \frac{1}{\hat{y}} \int_y (1 - F(y))^2 dy$, where \hat{y} is the mean income in the sample and $F(y)$ is the share of the population with income levels less than y . This measure has the interpretation as the area between the 45 degree curve (which indicates perfect equality) and the Lorenz curve.²

The Gini coefficient has the advantage of being invariant with respect to scale, so that larger areas or richer areas do not necessarily have larger or smaller Gini coefficients. Moreover, a ten percent increase in everyone's income will not impact the Gini coefficient. The Gini coefficient also always rises when income is transferred from a poorer person to a richer person. One standard criticism of the Gini coefficient is that the average Gini coefficient of a number of areas will not equal the Gini coefficient calculated for those areas all together.

There are several plausible alternatives such as the variance of income within an area ($\int_y (y - \hat{y})^2 dF(y)$) or the coefficient of variation ($\frac{1}{\hat{y}} \sqrt{\int_y (y - \hat{y})^2 dF(y)}$). The coefficient of variation, unlike the variance, will not increase or decrease if all incomes are scaled up or down by the same percentage amount. A final type of measure is the difference in income between individuals in different places of the income distribution,

² If we let p denote $F(y)$, i.e. the share of the population earning less than y , then the Lorenz curve plots the share of national income going to individuals earning less than $F^{-1}(p)$ as a function of p , i.e.

$$\frac{1}{\hat{y}} \int_{y \leq F^{-1}(p)} f(y) y dy.$$

for example the difference in income between people at the 90th and 10th, or the 75th and 25th, percentiles of the income distribution. We calculate these differences using the logarithm of income.

Using the 2000 Census five percent micro-sample, we calculate these five different income inequality measures at the metropolitan area level: (1) the Gini coefficient using household income, (2) the variance of household income, (3) the coefficient of variation of household income, (4) the income difference between the 90th and 10th percentiles of the household income distribution, calculated as the difference in the logs of these numbers and (5) the income difference between the log 75th and 25th percentiles of the household income distribution. Table 1 shows the correlation between our five measures as well as the correlation between these measures and the logarithm of both median family income in the area and population size.

The most reassuring fact in the table is that these income measures are fairly highly correlated. For example, the correlation coefficient between the Gini coefficient and the coefficient of variation is 92 percent. The correlation coefficient between the Gini coefficient and the 90-10 percentile income difference is 91 percent. The variance is less correlated with these other measures because it is highly correlated with the mean level of income in the area. In general, these different measures give us a similar picture of which metropolitan areas within the U.S. are most unequal.

We are interested not only in the stability of income inequality between different measures, but also in the stability of income inequality over time. Figure 2 graphs the Gini coefficient for 242 metropolitan areas estimated from the 1980 Census against the Gini coefficient from the 2006 American Community Survey, the most recent data available. For comparison, we also plot the 45 degree line.

Overall, the correlation between the Gini coefficient in 1980 and the Gini coefficient in 2006 is .58, which suggests neither extreme permanence nor enormous change in the rankings. Places that had an unusually high level of income inequality in 1980 revert

slightly to mean and have relatively less inequality today. As the Gini coefficient in 1980 increases by .1, the growth in the Gini coefficient over the next 26 years falls by .03. Some of the impermanence (and mean reversion) surely reflects measurement error in the Gini coefficient.

The most striking fact in Figure 2 is that the points in the graph are above the line in all but one area (Ocala, Florida), which means that for almost all the MSAs the estimated Gini coefficient is much higher today than it was 26 years ago. Much of this surely reflects the real increase in inequality in this country that has been extensively documented (e.g. in Katz and Murphy, 1992, and subsequent literature). However, some of the seeming increase in Gini coefficients may reflect changing top codes, but when we look at other measures that are less subject to top-coding issues (i.e. the 90-10 differences) we continue to see large increases in inequality in almost all areas.

In 1980, the Gini coefficients ranged from .33 to .45. Wisconsin had the most equal metropolitan areas 25 years ago with the Appleton-Oshkosh-Neenah MSA's Gini coefficient of .33, and Gainesville, Florida, was the most unequal metropolitan area with a Gini coefficient of .45. Two very poor Texas areas (Brownsville and McAllen) had the next highest levels of inequality. Wisconsin still has the country's most equal metropolitan area in 2006 (Sheboygan with coefficient of .38), but even it is substantially less equal than the most egalitarian places were 25 years ago. New Haven-Bridgeport-Stamford, with its combination of inner-city poverty and hedge-fund entrepreneurs, is now the most unequal metropolitan area in the country with a Gini coefficient of .54. While the county of Manhattan is more unequal, there are no other metropolitan areas that are even close to that Connecticut area in income inequality. The next three most unequal areas are Gainesville, Florida; Athens, Georgia; and Tuscaloosa, Alabama. Inequality shows up both in America's richest metropolitan areas, like New Haven, and in some of its poorer areas.

Generally, there is a negative association between area inequality and average incomes. For example, the Gini coefficient, coefficient of variation, the 90-10 percentile income

difference and the 75-25 percentile income difference are all negatively associated with area income. Figure 3 shows the -14 percent correlation between the Gini coefficient and the logarithm of median family income.

However, this connection has been declining over time. Figure 4 shows the -59 percent correlation between the Gini coefficient and the logarithm of median family income in 1980. This correlation is far stronger than the -14 percent correlation for 2006 shown in Figure 3. 25 years ago almost all rich places were relatively equal, given the relative inequality of the United States. Today, some of America's richest places are also among the most unequal. Some of this change may reflect changing top-coding, but it surely also reflects the enormous gains in wealth at the top end of the income distribution over the past 25 years in wealthy cities like San Francisco.

While the link between average income and inequality is becoming weaker, the link between area population and inequality is becoming stronger. In 1980, the raw correlation between population and the Gini coefficient was essentially zero (-.02). In 2000, the Gini coefficient's 15 percent correlation with area population is shown in Figure 5. Regressions (1) and (2) in Table 2 show bivariate regressions where the Gini coefficient is regressed on contemporaneous income and population measures in 1980 and today. Between 1980 and 2000, the connection between average income and the Gini coefficient fell by more than 40 percent, and the connection between area population and the Gini coefficient increased by roughly the same percentage.

Does nominal income inequality imply inequality of real incomes or of consumption? Prices differ across metropolitan areas, but if prices were the same for every type of person in every area, then prices should not impact inequality, at least as measured by the coefficient of variation or the Gini coefficient. However, as suggested by Black, Kolesnikova and Taylor (2007), prices may be quite different for people at different places in the income distribution. New York may be much more expensive for a relatively rich person than it is for a relatively poor person. Indeed, the very fact that

poor people continue to live in New York suggests that the area may not be as expensive for them as average prices would indicate.

This issue could be addressed by developing different price indices for people at different levels of the income distribution in different metropolitan areas, but that is far beyond the scope of this paper. Instead, we have undertaken the far simpler task of asking about the inequality of consumption of one important good: housing. If places with more rich people are expensive places for the rich to live, then we should expect to see less inequality of housing consumption than inequality of income.

To calculate a housing consumption Gini coefficient, we must first calculate a measure of housing consumption for everyone in the U.S. We start with a national housing price regression, where the logarithm of housing price is regressed on the characteristics of every household. Because of the limited number of housing characteristic data available from the Census microsample, we instead use data for 46 of the largest metropolitan areas from the American Housing Survey Metropolitan Samples for 1998, 2002, 2003 and 2004. Housing characteristics include interior square footage, exterior square footage, the number of bathrooms, the number of bedrooms and several other features. We then use this regression to form a predicted housing price measure for every household. Essentially, we are using a hedonic regression to create a housing price index that enables us to aggregate across different housing characteristics.

We use this housing consumption measure to calculate a Gini coefficient of housing consumption for every metropolitan area. Figure 6 shows the 38 percent correlation between this housing consumption Gini coefficient and our income Gini coefficient. More unequal incomes also have more unequal housing consumption, but in general housing consumption inequality is much less than income inequality and housing consumption inequality is particularly below income inequality in places with large amounts of income inequality. The mean housing consumption Gini coefficient is 0.28, much lower than 0.45, which is the mean of the household income Gini for this subsample of metropolitan areas in 2000.

While some of this difference can be attributed to measurement error, since our hedonic regression omits many key housing attributes, this result still suggests that places with highly unequal income levels have less housing consumption inequality than one might expect. This fact does not prove that prices are largely offsetting incomes, but heterogeneity in local prices that impact rich and poor people differently may be important, and measuring these prices and their impact is yet another interesting topic for future research.

III. The Causes of Urban Inequality

The typical economic approach to earnings is to assume that they reflect the interaction of human capital and the returns to human capital (e.g. Katz and Murphy, 1992). Indeed, human capital is often defined as including everything that goes into earnings, in which case the relationship is essentially tautological. If human capital is reduced to being a scalar, h , then the wage associated with each value of h is $w_i(h)$ where i represents each place. If the density of population in each area with human capital level h is $g_i(h)$, then the average earnings in a locality is equal to $\int_h w_i(h)g_i(h)dh$. The density of income will be $g_i(w_i^{-1}(y))$ where $G_i(w_i^{-1}(y))$ denotes the cumulative distribution of income.

If $w_i(h) = \alpha_i + \beta_i h$, then the variance of wages within a place is equal to $\beta_i^2 \text{Var}_i(h)$, where $\text{Var}_i(h)$ is the variance of h within place i . The coefficient of variation is

$\frac{\beta_i}{\alpha_i + \beta_i \hat{h}_i} \sqrt{\text{Var}_i(h)}$, where \hat{h}_i is the mean of h within place i . The Gini coefficient is

$1 - \frac{1}{\hat{y}_i} \int_y (1 - G_i(w_i^{-1}(y)))^2 dy$, and if h is distributed uniformly on the interval

$[\hat{h}_i - .5\sigma_i, \hat{h}_i + .5\sigma_i]$ then the Gini coefficient is $1 - \frac{(\beta_i)^3 \sigma_i}{3(\alpha_i + \beta_i \hat{h}_i)}$, which is a function of

both the distribution of skills and the returns to skill.

The inequality of after-tax, after-redistribution earnings will then also be affected by the progressivity of the tax rate and the state of the social safety net. We will turn to the heterogeneity in welfare payments later, but our primary focus is on the dispersion of before-tax earnings. We will begin by discussing the role that heterogeneous human capital plays in explaining the differences in inequality across space and the causes of that heterogeneous human capital. We will then turn to differential returns to human capital and governmental after-tax redistribution.

Human Capital Heterogeneity and Income Inequality Across Areas

To assess the role that human capital plays in explaining income inequality across areas, we will take two complementary approaches. First, we will simply regress the Gini coefficient on measures of human capital. Second, we will create Gini coefficients for each metropolitan area based on the observable measures of human capital and national wage regressions. Both measures are compromised by the fact that our measures of human capital are coarse. They capture only the years of formal schooling and years of experience. True human capital would include many more subtle factors, such as the quality of schooling and of experience.

In regression (3) of Table 2, we examine the relationship between the Gini coefficient in 2000 and two primary measures of human capital in the same year: the share of adults with college degrees and the share of adults who are high school graduates. We continue to control for area population and area income. Both of these variables are extremely significant and they increase the amount of variance explained (i.e. r-squared) from 15 percent to 49 percent. As such, more than one-third of the heterogeneity in income inequality across metropolitan areas can be explained by these two basic measures of human capital.

The coefficients are also large in magnitude. As the share of college graduates increases by 10 percent, the Gini coefficient rises by .031, a little more than one standard deviation.

As the share of high school graduates increases by 10 percent, the Gini coefficient drops by .018, about two-thirds of a standard deviation. While it may be unsurprising that even such crude proxies for heterogeneity in the human capital distribution can do so well at explaining the income distribution, this fact illustrates that much of inequality within an area reflects the heterogeneity of skills within that area.

One concern about results such as these is that perhaps the inequality of human capital within an area is itself an endogenous response to changes in the returns to skill. If places that have high returns to having a college degree attract people with college degrees, then controlling for the skill distribution in this way may also end up controlling for the returns to skill. After all, economic theory predicts that college graduates should go to places where the returns to being a college graduate are higher. Of course, this cannot explain why inequality is higher where there are more high school dropouts, but it is still worth taking the endogeneity of skills seriously.

One approach to this endogeneity is to look at long-standing historical skill patterns. We only have data on the share of the population with high school and college degrees going back to 1940. In regression (4), we show the results using those variables instead of contemporaneous college and high school graduation levels. We continue to control for contemporaneous income and population, but the results are unchanged if we remove those controls. Human capital levels in 1940 are still strongly correlated with inequality today. The overall r-squared declines to 32 percent, but these historical variables incrementally explain more than fifteen percent of the variation in the Gini coefficient.

The coefficient on the high school graduation rate in 1940 is quite close to the coefficient on 2000 high school graduation. The coefficient on the college graduation rate is more than three times higher using the older data. However, the variation in the college graduation rate is much smaller in 1940, so a one standard deviation increase in the college graduation rate has about the same effect when using 1940 or 2000 data. One way to understand why 1940 college graduation rates have such a strong impact on

modern inequality is that they strongly predict the growth in college graduation rates after that point.

In the fifth regression, we go back even further and look at 19th century measures of human capital. We do not have measures of human capital in the adult population, but we do have enrollment rates for high schools and colleges during this time period, which are found in historical Census data.³ Unfortunately, we lose over 70 metropolitan areas by using this historical data. The coefficients on these enrollment rates are not, therefore, particularly comparable with the coefficients on population-based skill measures in regressions (3) and (4). In regression (5), we find that the share of the population enrolled in college in 1850 is a quite solid predictor of income inequality today. High school enrollment rates also continue to negatively predict inequality.

In this case, the incremental r-squared created by those two variables when compared to regression (2) is quite modest (five percent). Still, we are impressed by the ability of 150-year-old educational variables, measuring something quite different from modern skill levels, to explain anything. The coefficient on college enrollment in 1850 is quite large, but again this needs to be considered together with the extremely small level of variation in this variable across space. These results continue to suggest to us that historical patterns of human capital play some role in explaining income inequality today.

In the sixth regression, we add two more historical measures of human capital: (1) the share of the population that is illiterate in 1850 and (2) the share of the population that was enslaved in that year. We interpret both measures as proxies for human capital deprivation. Learning to read is an obvious measure of human capital. Slaveowners often opposed education for their slaves. Indeed, during the century after emancipation, the former slave areas continued to provide particularly poor education for African-Americans. Both illiteracy and slavery in 1850 help predict inequality today. Adding

³ Haines, M.R., (2004) ICPSR study number #2896, Historical Demographic, Economic, and Social Data: The United States, 1790-2000.

these variables increases the r-squared of the regression to 26 percent, an additional six percent.

Another way of looking at the impact of human capital is to ask whether human capital in 1980 is associated with growth in inequality after that year. In Table 3 we regress the Gini coefficient in the year 2006 on the Gini coefficient in the year 1980 and other controls. We use the 2006 measure, rather than the 2000 measure, because it increases the time period of change by 30 percent. Regression (1) can be interpreted as a growth regression since we are asking about the determinants of inequality today, holding past inequality constant. The coefficient of .79 on the Gini coefficient in 1980 implies that there is mean reversion between 1980 and today, although this could be the result of measurement error. The result on income and population tell us that income inequality has been rising both in bigger areas and in richer areas.

In regression (2), we include our controls for human capital in 1980. Again, there is a strong positive association between college graduation rates in 1980 and inequality today. Places with more highly skilled people in 1980 have become more unequal over time, which presumably reflects both the rise in the returns to skill and the tendency of skilled people to move to more skilled areas, which we will discuss later. Places with more college dropouts have also become more unequal over time. Not only do contemporaneous skill levels predict inequality, but inequality of skills in 1980 predicts an increase in income inequality since then.

We now turn to our second means of assessing the importance of skill distributions in explaining the inequality of income. In this approach, we calculate only the income inequality from males between the ages of 25 and 55. To keep sample sizes up, we look only at the 102 metropolitan areas with more than 500,000 people. We use only workers with positive earnings, and we use only labor market income. We calculate three Gini coefficients. First, we calculate the standard Gini coefficient using the earnings from these workers. Figure 7 shows the 74 percent correlation between this Gini coefficient and our household income Gini coefficient among these 102 metropolitan areas.

We then compare this Gini coefficient for male workers with Gini coefficients based entirely on the human capital of these workers, by which we mean age and years of schooling. To calculate these “human capital only” Gini coefficients, we use a nationwide earning regression to predict earnings for everyone in the sample. By using these predicted earnings rather than true earnings we can isolate the impact of the level of human capital in an area while abstracting away from the differential returns to schooling. We calculate the Gini coefficient based on these predicted earnings. Figure 8 shows a 57 percent correlation between the two Gini coefficients.

Our Gini coefficient based only on human capital explains about 33 percent of the variation in overall income inequality among working-age males. This is a considerable amount of explanatory power, but it still leaves plenty to be explained. Another way of looking at the data is to note that the average Gini coefficient calculated with human capital only is one half the size of the Gini coefficient calculated using true income. As such, human capital gets you some, but far from all, of the way towards explaining the amount of income inequality.

One reason why these human capital based measures are failing to more fully explain actual income inequality might be that our human capital measures are so coarse. Occupations may provide us with a richer means of measuring individual-level human capital. As such, we created a third Gini coefficient using the same sample but including occupation dummies in our wage regressions. These dummies are then used, along with years of schooling and age, to predict wages, and these predicted wages are used to calculate a local Gini coefficient. The mean of this occupation-based Gini coefficient is about half-way between the Gini coefficient with just education and age and the Gini coefficient of true income. If we accept that occupation is a measure of skills, then this measure goes much more of the way towards explaining income inequality across areas.

Figure 9 shows the 86 percent correlation between this occupation-based Gini coefficient and the true income Gini coefficient. The occupation-based index has the ability to

explain 73 percent of the variation in the true income Gini coefficient. There are two interpretations of this finding. First, occupation may be proxying for income more than human capital and therefore should not be used as a control in the regression. Second, occupation may indeed be a better measure of human capital. There is surely some truth in both views, but we can draw the conclusion from this section that heterogeneity in human capital across space can explain a considerable amount of the heterogeneity in income inequality across space.

The Causes of Human Capital Inequality

Why are the levels of human capital so different in different places? One theory is that current human capital levels reflect long-standing education policies formed over the last 200 years; Goldin and Katz (2008) provide a rich description of this history. Urban and economists who emphasize people's location decisions will tend to focus on differences in economic productivity and differences in amenities that then motivate migration (e.g. Dahl, 2002). According to this view, areas that specialize in industries which are particularly good for low or high skill workers should then disproportionately attract those workers. Of course, this theory just pushes the puzzle one step backward. A more complete explanation for heterogeneity in skills would also explain why different industries are located in different places. In some cases, like cities with ports or coal mines, there are exogenous factors that explain industrial location, but observable variables tend to only explain a modest amount of industrial concentration (Ellison and Glaeser, 1999).

Alternatively, amenities may draw high-skill workers to a particular location. For example, if there is some amenity that is particularly desirable and in particularly short supply, then we would expect rich people to locate in places with that amenity. This can certainly explain why there are so many rich people in Paris (Brueckner, Thisse and Zenou, 1999) or on the Riviera. Alternatively, there can be other amenities, such as access to public transportation, which might draw poor people disproportionately to a given area.

While the economic framework that emphasizes rational location choice certainly has some ability to explain the distribution of skilled people across space, much of current skill patterns appear to be determined by long-standing historical skill patterns, as discussed above. For example, Figure 10 shows the 73 percent correlation between the share of adults with college degrees in the year 2000 and the share of adults with college degrees in the year 1940. The college share of the population in 1940 is able to explain more than 50 percent of the variation in the college share today, which suggests the enormous power of historical forces in shaping the skill composition of cities today.

We also run a regression that shows that skill growth is strongly predicted by the initial skill level. As the 1940 share of the adult population with college degrees increased by 5 percent, the growth rate in the share of the population with college degrees between 1940 and 2000 increased by 10 percent. Far from there being mean reversion in this variable, there has been a tendency of skill growth to be concentrated in places that began with more skills (Berry and Glaeser, 2005).

The relationship between today and the past is much weaker at the bottom end of the skill distribution. Figure 11 shows the 45 percent correlation between the share of the adult population who did not have a high school degree in 1940 and the share of the adult population without a high school degree in 2000. In this case, the 1940 variable can only explain one-fifth of the variation in the high school dropout rate today. The graph shows a number of places, such as Miami and McAllen, Texas, which have particularly large high school dropout rates today relative to their historical levels. Older variables, such as the percent of the population enslaved in 1850, can explain about one-tenth of the variation in the high school dropout rate today.

These outliers suggest that immigration, particularly from Latin America, is also associated with a heavy concentration of less skilled workers. Figure 12 shows the 57 percent correlation between the share of the population that is Hispanic and the share of the population without a high school degree in 2000. Together, the Hispanic share today

and the dropout rate in 1940 can explain 61 percent of the variation in the dropout rate today. The Hispanic share is particularly high in Florida, Texas and California, which are three states that were once part of the Spanish Empire and which are geographically close to Mexico and other countries in Latin America. In fact, the correlation between Hispanic share and MSAs latitude is -36 percent, which reinforces this point. Once again, history seems to play a large role in explaining the current skill distribution.

By contrast, the evidence supporting the importance of the traditional economic explanations of the location of talent is much weaker. For example, there is little evidence that highly skilled people have moved to areas with particularly pleasant temperatures. There is a no robust association between January temperature and the share of the population with college degrees. High July temperatures are associated with fewer college graduates, but even this effect is quite modest. July temperatures can explain only 6.5 percent of the variation in the share of the population with college degrees.

LeRoy and Sonstelie (1983) and Glaeser, Kahn and Rappaport (2008) provide theory and evidence supporting the view that less skilled people live in the centers of metropolitan areas because of access to public transportation. Cars are expensive, and poorer people prefer the time-intensive, lower-cost alternative of buses and subways. Can access to public transportation explain the location of less-skilled people across areas? No. There is virtually no correlation across metropolitan areas between the share of the population without high school degrees and the share of the population that takes public transportation. This absence of correlation is particularly surprising since the poor generally take public transit more, which should yield a positive relationship between less skilled people and public transit, even if the poor didn't move across metropolitan areas in response to public transit access.

Alternatively, people of different skill levels may be drawn to particular areas because of skill-specific economic opportunities. Silicon Valley has a booming computer industry, and it attracts extremely highly skilled engineers. New York City attracts smart people to

work in finance. Certainly, there is a strong correlation between the skill level of an area and the skill orientation of the industries in the area. Using the 2000 Census, Glaeser and Gottlieb (2008) ranked industries by the share of the workers in that industry in the nation with a college degree. They then calculated the share of a metropolitan area's employment that was in the top 25 percent industries ranked by human capital and in the bottom 25 percent of industries ranked by human capital.

Figure 13 shows the 79 percent correlation between this measure of high skilled industries and the share of the population with college degrees. Figure 14 shows 49 percent correlation between the share of the adult population without a college degree and the measure of low-skill industries. Certainly, there is a robust relationship between the skill orientation of the industries in an area and the skill distribution of the area. But which way does the causality run? Are skilled industries moving into an area because there are an abundance of skilled workers, or are skilled workers moving to areas because of skill-oriented industries?

While surely both phenomena occur, we think that the evidence supports the view that industries are responding to the area's skill distribution more than the view that the skill distribution is responding to the area's industries mix. For example, the share of the population with college degrees in 1940 can explain 35 percent of the variation in the skill mix of industries today. By contrast, the skill composition of the industries in the metropolitan area in 1980 can only explain seven percent of the variation in growth of the population with college degrees since that date. The complex two-sided nature of this relationship makes it difficult to accurately assess the direction of causality, but there are reasons to think that much of the industrial mix in the area is actually responding to the skill distribution.

One variable that seems more plausibly predetermined is the concentration in manufacturing during the first half of the 20th century. The location of factories does not seem likely to be particularly driven by the presence of highly skilled workers 100 years ago. Yet an industrial orientation, as late as 1950, is negatively correlated with the share

of the population with college degrees today, perhaps because those manufacturing cities tended not to reinvent themselves as centers of idea-oriented industries or perhaps because manufacturing employers were less disposed towards high schools earlier in the century (Goldin and Katz, 2008). As the share of the workforce in manufacturing in 1950 increases by 10 percent, the share of the population with college degrees drops by about 1 percent. This may explain why, as shown in Table 2, Regression (7), manufacturing in 1950 is negatively associated with inequality today.

These industrial measures are essentially proxies for differential returns to human capital across metropolitan areas. Using wage regressions, we are able to estimate such differential returns directly by running regressions of the form:

$$(1) \text{Log}(Wage) = \alpha_{MSA} + \beta_{MSA}^{BA} * BA\text{Grad} + \beta_{MSA}^{HS} * HS\text{Grad} + \text{Other Controls}$$

where α_{MSA} is an area specific intercept, β_{MSA}^{BA} is an area specific return to having a college degree and β_{MSA}^{HS} is an area specific return to having a high school diploma. This regression estimates a differential return to different levels of schooling for each metropolitan area. We estimate this regression only for prime age males, and include controls for experience. We focus only on those areas with more than 500,000 people so that the returns to schooling are estimated with reasonable precision.

Figure 15 shows the 24 percent correlation between our estimate of β_{MSA}^{BA} and the share of the adult population with college degrees in the 102 metropolitan areas in our sample with more than 500,000 people. One interpretation of this fact is that skilled people are moving to places where the skill levels are higher. A second interpretation is that agglomerations of skilled people raise the returns to skill. Any interpretation of this relationship is compromised further by the fact that an abundance of skilled people would normally reduce the returns to skill in a typical model of labor demand. Still, this does suggest that highly skilled people are living in places where the returns to skill are higher.

Differential Returns to Human Capital

The fact that the returns to capital differ across space can also potentially explain the inequality that we see across metropolitan areas. As the formula discussed above illustrates, pre-tax income inequality will reflect both differences in the distribution of skills and differences in the returns to those skills. Certainly, the framework predicts a strong link between places with higher returns to college and income inequality.

Figure 16 shows the 73 percent correlation between our estimated return to a college degree and the Gini coefficient across the 102 areas with more than 500,000 people. The measured return to a college degree is much better at explaining area inequality than the number of people with college degrees. Of course, these returns are directly based on the same income data that is being used to generate the Gini coefficient. Still, this finding seems to confirm the view that heterogeneity in returns to skill can help us to explain differences in income inequality across space.

To look at this further, we again calculate Gini coefficients for each metropolitan area using wage regressions. However, in this case, we allow the coefficients on skills to differ across metropolitan areas as shown in equation (1) above. We again run these regressions only for prime aged males. We then use these regressions to predict the amount of inequality in an area if the skill distribution of the area were the same as the skill distribution in the country as a whole. When we calculated Gini coefficients using wage regressions above, we were calculating local Gini coefficients based only on differences in the skill composition, holding the returns to skill constant across space. Now we calculate Gini coefficients holding the skill composition constant, but allowing the returns to skill to differ across space.

Figure 17 shows the 71 percent correlation between these predicted wage Gini coefficients and actual Gini coefficients in our sample of prime age males across metropolitan areas with more than 500,000 people. The relationship is tighter than it was when we looked at Gini coefficients that assumed a constant return to skill. Moreover,

this Gini coefficient holding the skill composition constant explains 50 percent of the variation in the actual Gini coefficient, whereas our constant return to skills Gini explained only 33 percent of the difference. We interpret these results as suggesting that differential measured returns to human capital can explain area-level income inequality somewhat better than differences in measured human capital.

One potential concern with interpreting these results is that measured returns to human capital may not be measuring higher returns to human capital, but instead measuring high levels of true human capital associated with each coarse category of observed human capital. For example, if people with college degrees in some areas went to higher quality schools or have had better work experience, then this would cause the measured return to a college education to increase, even if the true returns to human capital were constant across space. We have no way of dealing with this hypothesis, and we will continue referring to the measured returns to human capital as the returns to human capital, understanding that it can also reflect other things.

While differences in the returns to skill do seem to explain a significant amount of the differences in inequality, we do not know what explains differences in returns to skill across space. For example, the positive correlation between the share of the population with college degrees and returns to skill might suggest that being around other skilled people increases the returns to being skilled. Alternatively, Beaudry, Doms and Lewis (2006) suggest that places with abundant skilled workers invested in computerization, which then had the effect of raising the returns to skill. While we are certainly sympathetic to these interpretations, it is hard to distinguish between this view and the view that more skilled people are moving to areas where the returns to skill are higher.

Moreover, the share of the population with college degrees in 1940 does little to explain the returns to college today. If we thought that higher returns to skill reflected the power of agglomerations of skilled people, then an abundance of skills in 1940, which predicts skills today, should also predict higher returns to college today. This is not the case, as we find only a 5 percent correlation between the share of the population with a college

degree in 1940 and our measure of the return to a college degree. Instead, a higher return to college today is strongly associated with recent growth in the share of the population with college degrees. The correlation between our return to college measure and the change in the proportion of the adult population with college degrees is 26 percent. These facts support the idea that skilled people are moving to areas where the returns to skill are higher.

Other variables also do a relatively poor job of explaining the returns to skill. For example, our measure of skill intensive industries doesn't explain the returns to skills. Looking at Figure 15 shows that some of the places with the highest returns to skill are usual suspects. The financial agglomeration in Southwestern Connecticut and the technology agglomeration in San Francisco Bay have very high returns to human capital. But there are also areas, like Houston and Birmingham, that are more of a surprise.⁴

Figure 18 illustrates the 34 percent correlation between our estimated returns to college and the share of workers in finance among the 102 cities in our sample with more than 500,000 people.⁵ Figure 19 shows the 27 percent correlation between the returns to college and the share of workers in the computer industry among the same sample of cities.⁶ This seems to support the results of Beaudry, Dom and Lewis (2006) who show a link between computerization and inequality. A related and interesting hypothesis is that wage inequality is linked to the former concentration of low skilled workers in routine tasks that have now been made obsolete (Autor and Dorn, 2007).

Still, we are much more confident that differences in the returns to skill can explain a significant amount of income inequality across metropolitan areas than we are in explaining why areas have such different returns to human capital. A number of recent papers, like Autor and Dorn (2007); Black, Kolesnikova and Taylor (2007); and Beaudry,

⁴ Like Black, Kolesnikova and Taylor (2007), we find a modest positive relationship between cost of living and returns to college.

⁵ "Finance" is defined using IPUMS 2000 Occupation Codes for the 5% sample at <http://usa.ipums.org/usa/volii/00occup.shtml>. Finance codes are 12, and 80-95.

⁶ "Computers" is also defined using IPUMS 2000 Occupation Codes for the 5% sample at <http://usa.ipums.org/usa/volii/00occup.shtml>. Computer codes are 11, 100-111, and 140.

Dom and Lewis (2006) have brought some understanding to this question, but it remains a pressing topic for future research.

IV. The Consequences of Urban Inequality

At the national level, income inequality has been linked to low levels of economic growth, perhaps because inequality leads to political strife (Persson and Tabellini, 1994; Alesina and Rodrik, 1994), but local inequality is not the same thing as national inequality. No one should be surprised if the political and economic effects of inequality are different at the local level. After all, local political outcomes are far more constrained by state constitutions and easy out-migration.

More generally, local inequality, as opposed to local poverty, is not necessarily a bad thing. If people of different income levels mix throughout the country, then local inequality will be higher than if people segregate into homogenous, stratified communities. A large number of studies suggest economic mixing, i.e. local inequality, benefits the less fortunate by giving them more successful role models (Wilson, 1987) or employers (Mazzolari and Ragusa, 2007). Others suggest that the wealthy develop empathy for the poor through spatial proximity (Glaeser, 1999). Egalitarians can simultaneously hope for policies that would reduce inequality at the national level, such as increasing the schooling levels for least fortunate, while opposing policies that would reduce local income inequality by moving rich people away from poor people.

Persson and Tabellini (1994) found a strong negative relationship between national income inequality and economic growth. Some facts about urban growth are quite similar to facts about country growth. For example, schooling predicts growth at both the country and the city level. Does the connection between inequality and growth carry over to the metropolitan level?

In Table 4, we look at the relationship between inequality and growth across our sample of metropolitan areas. We use 1980 as our start date and look at the growth of both

income and population after that year. While country-level regressions typically look only at income growth, city level growth regressions look at population and income (and sometimes housing values as well), since increases in productivity should show up both in higher wages and in more people.

The first regression of Table 4 shows that the raw relationship between income inequality and local area growth is positive. Places with more inequality have been gaining population. However, as the second regression in Table 4 shows, this result is not robust to including a number of other city level controls, such as human capital variables and January temperature. With these controls, inequality has a significant negative effect on area population growth. The next two regressions in Table 4 show the relationship between inequality and area income growth. After including area level controls, inequality has a significant negative impact on income growth. The coefficients here should be interpreted while keeping in mind the relatively low level of variation in the 1980 Gini variable. Going all the way from the bottom of the inequality distribution at 0.33, to the top of the distribution at .45, would cause population growth to fall by about 1 standard deviation.

These results do suggest that income inequality is only negatively correlated with area growth once we control for skills. Increases in the skill distribution that make a place more unequal by increasing the share of highly educated citizens are associated with increased, not decreased, growth. However, growth of both income and population was lower in places where the income distribution is particularly unequal, holding skills constant.

A second adverse consequence of inequality at the country level is the connection between inequality and crime (Fajnzylber, Lederman and Lloayza, 2002). These results have also been found at the metropolitan area level (Daly, Wilson and Vasdev, 2001). We duplicate them here.

In regression (5) of Table 4, we show the strong positive relationship between income inequality and murder rates across metropolitan areas. We focus on murder rates because they are the most serious crime outcome and the outcome that is least likely to be impacted by reporting differences across areas. The 35 percent correlation, shown in Figure 20 is quite strong. Regression (6) of Table 4 shows that the inequality-crime relationship is robust to a number of other controls.

Why do murder rates increase with inequality? One view is that inequality is just proxying for poverty, but both at the country and city level, the impact of inequality on crime survives controls for the mean income level and the poverty rate. A second explanation is that inequality leads to less focus on providing community-wide public goods, like policing. A third explanation is that inequality breeds resentment which then shows up in higher murder rates.

All of these explanations remain speculation, but there is some evidence that links unhappiness to envying richer neighbors. Luttmer (2005) looks at the self-reported happiness of individuals as a function of the wealth of their neighbors. He finds that people who have richer peers are more likely to say that they are unhappy. The existence of envy can, under some conditions, suggest that sorting by income is preferable to highly unequal areas.⁷

In Figure 21, we show the -47 percent correlation between the Gini coefficient and the average self-reported happiness in the metropolitan area taken from the General Social Survey. These happiness data span the last 25 years, and they represent the share of people who say that they are very happy. Inequality can explain 22 percent of the variation in this unhappiness measure, and this result is robust to a reasonable number of other controls such as average area income and population size.

V. Government Policy

⁷ We have also looked at whether there is a correlation between income inequality and racial segregation, using dissimilarity measures of segregation (see Cutler, Glaeser and Vigdor, 1999 for details of the measure). We find no evidence of any such connection.

There are two ways in which government policy interacts with the study of urban inequality. First, government policy may itself be a cause of that inequality. Second, if policy makers seek to reduce local inequality, then the study of that inequality may improve the quality of decision-making. We start with a discussion of the role that governmental actions might have on the level of inequality and then turn to a discussion of potential policy implications.

Government Policies and Local Inequality

There are at least three channels through which government policy might impact the degree of income inequality across space. First, education is largely a government service, and government policies towards education could either widen or narrow the distribution of skills within an area. Second, government policies can also impact migration in ways that might increase or decrease the skill distribution. Third, the government engages in taxes and redistribution, which would impact the after-tax income distribution. Some of these policies are explicitly intended to impact inequality, and other policies are intended to achieve different results but still could end up changing the level of local inequality.

Investment in school certainly appears to impact the distribution of skills within an area. For example, Moretti (2004) shows that the presence of a land-grant college in a metropolitan area prior to 1940 is positively correlated with the skill level of the area today. When we regress the area Gini coefficient on Moretti's land-grant college indicator variable, controlling for area population, income and the share of adults who are high school dropouts, we find a positive, but statistically insignificant, impact of land grant colleges on inequality. This effect disappears when we control for share of adults with college degrees, which implies that this variable (weakly) increases inequality because it increases the share of more skilled people.

Conversely, we find a modest negative relationship between current high school enrollment rates and inequality when we control for area income and area population. This result may reflect the tendency of poverty to lead to low enrollment rates or the tendency of middle income people to move to areas with fewer dropouts or the ability of high school graduation to reduce inequality. We will not try to distinguish these hypotheses but just point out that correlations of this form suggest that education policy can surely impact inequality, both by its direct effect on the skill distribution and by shifting migration patterns.

There is a long economic literature that suggests that different local level government policies have the ability to induce selective migration. For example, Borjas (1999) argues that heterogeneity in welfare policies across space has had a huge impact on the location patterns of less skilled immigrants, and especially their tendency to locate in California. Blank (1988) also found that higher welfare levels impact the location decision of unmarried women with children. This type of effect can explain the poverty of East St. Louis, which traditionally had higher welfare payments because it lies on the Illinois side of the Mississippi River within the St. Louis metropolitan area.

Less work has been done on the impact of redistribution on the location decisions of the rich, but what evidence does exist supports the view that the wealthy are quite mobile and respond to attempts at redistribution. Certainly, within metropolitan areas, there are good reasons to think that the rich are sensitive to local tax rates and the bundle of local public goods. The strong tendency of richer people to live outside of city borders suggests that they are voting with their feet within certain areas. Haughwout et al. (2004) argue that these migration tendencies are quite strong and can mean that areas can actually lose revenue by raising taxes. Feldstein and Wrobal (1998) argue that the migration elasticities are so strong that states cannot effectively redistribute income at all. This type of result supports the view that local governments can affect local inequality by moving people more than they can by classical redistribution.

The connection between government policies and local income inequality is in many ways an understudied topic. We certainly know something about the impact of education, and we know much about migration responses to local policy differences, but we do not understand the full contribution that government has played in making some places more or less equal. For example, local land-use controls that prevent housing for lower income people can create less inequality within an area, but we do not know how empirically important this might be.

Local Governments and Local Inequality

Localities do have tools with which they could reduce local income inequality, but it is not obvious that such tools would enhance welfare. For example, the preceding analysis suggested that much of the heterogeneity in income inequality across metropolitan areas was associated with differences in returns to skill. Localities could equalize local incomes by reducing the returns to skill through more redistributive taxation. Redistribution would both directly reduce inequality, and is likely to also reduce inequality by inducing wealthier people to leave the area. However, few localities would actually find it attractive to increase equality by getting rid of the biggest tax-payers. While this migration effect might reduce inequality, if it eliminated the richest people in the city, there are many reasons to think that it would also hurt the area's economy.

The returns to skill were not closely tied to industrial mix, so trying to attract particular industries doesn't seem likely to lead to significant changes in inequality. Moreover, the historical track record of local industrial policy is decidedly mixed. A long tradition of urban analysis suggests that localities have a very limited ability to make society more equal (Peterson, 1981). The ability of wealthy people to flee is just too great.

Greater welfare gains would seem to be associated with policies that enhanced the skills of the less fortunate. Improvements in school districts and reductions in the size of the criminal sector could have two possible benefits. First, they might increase the skill levels at the bottom end of the income distribution. Second, they might attract middle-

income people into the area. Local policies that strengthened the bottom of the income distribution without targeting the top of the income distribution seem most likely to reduce income inequality without creating other problems.

However, while such policies might well be beneficial, local governments have again only a limited ability to make the nation-wide skill distribution more equal. Areas with many poor parents have fewer resources with which to educate their children. These places have lower tax revenues, holding everything else constant, but they also have less parental human capital on which to draw. The long-noted power of peers means that places with lower initial skill distributions inevitably have difficulty creating first rate public schools.

National Governments and Inequality

Even if one accepts egalitarian ideas that inequality is itself a bad thing, it certainly does not follow that reducing local inequality is clearly desirable. Would it be sensible for national government policies to artificially segregate rich people into some cities and poor people into others? Such segregationist policies would increase equality at the lower level, but it is hard to see how they would increase local welfare levels. Some of our regressions have suggested that localities will grow more quickly and have less crime if they are more equal, but even these results must be treated gingerly. National policies that created equality by removing high skill, high earnings workers from power areas would also be likely to reduce the economic performance of those areas. Policies that reduce the numbers of poor people by eliminating urban attributes that attract those people, like low-cost housing, would also have negative consequences, most notably the destruction of a valuable asset that is providing some benefit for the least fortunate members of society.

At the national level, egalitarianism suggests simple, non-spatial policies, such as classic income redistribution and policies that support human capital accumulation among the least fortunate. National policies can also reduce income inequality through

redistributive taxation. Those policies involve costs and benefits, and their connection with cities and localities is relatively modest, since local attempts at redistribution are likely to create emigration of the wealthy.

Long term reductions in inequality are most likely to be achieved through a more egalitarian distribution of human capital. Naturally, changes in the distribution of human capital will take years, if not decades. Those changes will also involve the often uncomfortable cooperation of national and local governments. Attempts to reduce inequality by changing the skill distribution must considerably involve localities, given our current decentralized schooling system. Yet, localities rarely have the resources to significantly upgrade their schools on their own.

The current structure of local public schooling creates incentives for middle income people to leave big cities to get better schools for their children. The poor and the very rich, who send their children to private schools, remain. There could be welfare gains from an education system that kept the advantages of choice and competition that are associated with the current system but that also reduced the incentive for middle class parents to leave big cities.

This fact is the great challenge facing attempts to reduce inequality through schooling. Our schools are local and localities have a great deal of trouble dealing with inequality. Poor places have fewer resources to allocate to their schools. Yet if there is going to be a more equal education distribution, then their schools must be improved. Creating equality in human capital requires the difficult cooperation of national level education policy, and schools that often operate at a very local level.

VI. Conclusion

In this essay, we have reviewed the economic causes of metropolitan-area income inequality. Differences in income inequality across areas can be explained well by both differences in the skill distribution and differences in the returns to skill. If anything,

differences in the returns to skill appear to be more important in explaining the variation in the Gini coefficient across American metropolitan areas. Differences in the skill distribution can be well explained by historical tendencies towards having more skilled people and by immigration patterns. Differences in the returns to skill are far more difficult to explain, but today the returns to a college degree are highest in areas that specialize in finance or computing.

There are some negative correlates of area-level inequality. More unequal places have higher murder rates, and people say that they are less happy. More unequal places grow more slowly, at least once we control for the skill distribution in an area. The raw correlation between area-level inequality and population growth is positive.

Area-level income inequality does not create the same policy implications as national income inequality. At the nation level, an egalitarian, Rawlsian social welfare function implies the need to reduce income inequality. However, egalitarianism does not provide the same implications about local inequality. Shuffling people across the country in a way that creates more homogeneity at the local level would not seem like a natural means of increasing social welfare given standard social welfare functions. Instead, such functions would instead push towards a focus on policies like human capital development that would promote equality nationwide.

We concluded by noting that localities are poorly poised to reduce inequality on their own. Any attempt at local redistribution is likely to lead to out-migration of the wealthy. Poor localities don't have the resources to improve failing schools.

However, if national policies are going to try to reduce inequality by making the distribution of human capital more equal, then inevitably localities must be involved. Schools are run at the local level. The combination of national resources and local operation seems most likely to improve the quality of the poorly performing schools. Unfortunately, bringing together such different levels of government is inevitably quite difficult. Moreover, the strong correlation between human capital today and human

capital more than fifty years ago suggests that any change will not happen overnight.

References

- Alesina, A., Glaeser, E. L., 2004. *Fighting Poverty in the U.S. and Europe: A World of Difference*. Oxford University Press, New York, NY.
- Alesina, A., Rodrik, D., 1994. "Distributive Politics and Economic Growth." *Quarterly Journal of Economics* 109(2), 465-490.
- Autor, D., Dorn, D., 2007. *Inequality and Specialization: The Growth of Low-Skill Service Jobs in the United States*, MIT mimeograph.
- Beaudry, P., Doms, M. E., Lewis, E. G., 2006. *Endogenous Skill Bias in Technology Adoption: City-Level Evidence from the IT Revolution*. NBER working paper.
- Berry, C., Glaeser, E. L., 2005. "The Divergence of Human Capital Levels Across Cities." *Papers in Regional Science* 84(3), 407-444.
- Black, D., Kolesnikova, N., Taylor, L. J., 2007. *Earnings Functions When Wages and Prices Vary by Location*. Federal Reserve Bank of St. Louis working papers.
- Blank, R. M., 1988. "The Effect of Welfare and Wage Levels on the Location Decisions of Female-headed Households." *Journal of Urban Economics* 24(2), 186-211.
- Borjas, G. J., 1999. "Immigration and Welfare Magnets." *Journal of Labor Economics* 17(4), 607-637.
- Brueckner, J.K., Thisse, J-F., Zenou, Y., 1999. "Why is central Paris rich and downtown Detroit poor? An amenity-based theory." *European Economic Review* 43, 91-107.
- Cutler, D., Glaeser, E. L., Vigdor, J., 1999. "The Rise and Decline of the American Ghetto." *Journal of Political Economy* 107, 455-506.
- Dahl, G., 2002. "Mobility and the Return to Education: Testing a Roy Model with Multiple Markets." *Econometrica* 70(6), 2367-2420.
- Daly, M., Wilson, M., Vasdev, S., 2001. "Income inequality and homicide rates in Canada and the United States." *Canadian Journal of Criminology*, 219-236.
- Ellison, G., Glaeser, E. L., 1999. "The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration?" *American Economic Review Papers and Proceedings* 89(2), 311-316.
- Fajnzylber, P., Lederman, D., Loayza, N., 2002. "Inequality and Violent Crime." *Journal of Law and Economics* 45(1), 1-40.

- Feldstein, M., Wrobel, M.V., 1998. "Can State Taxes Redistribute Income?" *Journal of Public Economics* 68(3), 369-396
- Glaeser, E. L., 1999. "The Future of Urban Research: Nonmarket Interactions." *Brookings-Wharton Papers on Urban Affairs*, 101-149.
- Glaeser, E. L., Gottlieb, J. D., 2008. "The Economics of Place-Making Policies." *Brookings Papers on Economic Activity*.
- Glaeser, E. L., Kahn, M. E., Rappaport, J., 2008. "Why do the Poor Live in Cities? The role of Public Transportation." *Journal of Urban Economics* 63(1), 1-24.
- Goldin, C. and L. Katz (2008) *The Race between Education and Technology*. Cambridge: Harvard University Press.
- Haines, M. R., 2004. "Historical, Demographic, Economic, and Social Data: The United States, 1790-2000." Inter-University Consortium for Political and Social Data, <http://www.icpsr.umich.edu/cocoon/ICPSR/STUDY/02896.xml>.
- Haughwout, A., Inman, R., Craig, S., Luce, T., 2004. "Local Revenue Hills: Evidence from Four U.S. Cities." *The Review of Economics and Statistics* 86(2), 570-585.
- Katz, L., Murphy, K., 1992. "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." *Quarterly Journal of Economics* 107(1), 35-78.
- LeRoy, S. F., Sonstelie, J., "1983. Paradise Lost and Regained: Transportation Innovation, Income and Residential Location." *Journal of Urban Economics* 13, 67-89.
- Luttmer, E. F. P., 2005. "Neighbors as Negatives: Relative Earnings and Well-Being." *Quarterly Journal of Economics* 120(3), 963-1002
- Mazzolari, F., Ragusa, G., 2007. "Spillovers from High-Skill Consumption to Low-Skill Labor Markets." *IZA Discussion Paper* 3048.
- Moretti, E., 2004. "Estimating the Social Return to Higher Education: Evidence From Cross-Sectional and Longitudinal Data." *Journal of Econometrics* 121(1-2), 175-212.
- Peterson, P. 1981. *City Limits*. Chicago: University of Chicago Press.
- Persson, T., Tabellini, G., 1994. "Is Inequality Harmful for Growth?" *American Economic Review* 84(3), 600-621.
- Ruggles, S., Sobek, M., Alexander, T., Fitch, C. A., Goeken, R., Hall, P. K., King, M., Ronnander, 2008. *Integrated Public Use Microdata Series*, <http://usa.ipums.org/usa>

Wheeler, C., 2005. "Cities, Skills and Inequality." *Growth and Change* 36(3), 329-353.

Wilson, W. J., 1987. *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy*. Chicago University Press, Chicago, IL.

Table 1
Table of Correlations Between Income Inequality Measures for 2000

	Gini Coefficient	Variance of Household Income	Coefficient of the Variation of Household Income	Difference of the Log of Income for the 90th and the 10th Percentiles	Difference of the Log of Income for the 75th and the 25th Percentiles	Log of Median Family Income	Log of Population
Gini Coefficient	1						
Variance of Household Income	0.36	1					
Coefficient of the Variation of Household Income	0.92	0.20	1				
Difference of the Log of Income for the 90th and the 10th Percentiles	0.91	0.29	0.74	1			
Difference of the Log of Income for the 75th and the 25th Percentiles	0.86	0.13	0.72	0.93	1		
Log of Median Family Income	-0.25	0.68	-0.44	-0.17	-0.28	1	
Log of Population	0.15	0.57	0.04	0.12	0.00	0.44	1

Source: The Gini coefficient, variance of household income, the coefficient of the variation of household income, the difference of the log of income for the 90th and 10th percentiles and the difference of the log of income for the 75th and 25th percentiles are calculated using the 5% Integrated Public Use Microdata Series (IPUMS) for 2000, at usa.ipums.org. Median family income and population are from the 2000 Census.

Table 2
Causes of Urban Inequality

	1980 Gini Coefficient		2000 Gini Coefficient				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln(1980 Population)	0.0055 [0.0012]**						
Ln(1980 Median Family Income)	-0.1078 [0.0084]**						
Ln(2000 Population)		0.0081 [0.0016]**	0.005 [0.0013]**	0.0075 [0.0014]**	0.0085 [0.0019]**	0.0078 [0.0018]**	0.008 [0.0015]**
Ln(2000 Med. Family Income)		-0.0625 [0.0096]**	-0.1054 [0.0112]**	-0.0773 [0.0091]**	-0.0602 [0.0131]**	-0.0392 [0.0139]**	-0.0525 [0.0096]**
2000 Pct. Of 25+ Pop. With BA			0.3122 [0.0233]**				
2000 Pct. Of 25+ Pop. With HS			-0.1842 [0.0257]**				
1940 Pct. Of 25+ Pop. With BA				1.1176 [0.1337]**			
1940 Pct. Of 25+ Pop. With HS				-0.1906 [0.0329]**			
1850 Pct. Of Pop. Enrolled in College					3.0137 [0.8351]**	2.4933 [0.8285]**	
1850 Pct. Of Pop. Enrolled in HS					-0.0499 [0.0173]**	-0.0129 [0.0194]	
1850 Illiteracy Rate						0.061 [0.0327]	
1850 Pct. Of Pop. Enslaved						0.0372 [0.0102]**	
Share of labor force in manufacturing, 1950							-0.0447 [0.0109]**
Constant	1.3835 [0.0782]**	1.013 [0.0960]**	1.5937 [0.1045]**	1.1751 [0.0917]**	0.9877 [0.1311]**	0.7564 [0.1411]**	0.9174 [0.0960]**
Observations	258	282	282	281	208	208	281
R-squared	0.39	0.15	0.49	0.32	0.2	0.26	0.19

Notes:
Standard errors in brackets. * significant at 5%; ** significant at 1%

Source: The Gini coefficients are calculated using the 5% Integrated Public Use Microdata Series for 1980 and 2000, at usa.ipums.org. Other 1980 variables are from the 1980 Census, and other 2000 variables are from the 2000 Census. All other variables are from Haines, M.R., ICPSR study number 2896, Historical, Demographic, Economic, and Social Data: The United States, 1790-2000.

Table 3*Changes in Inequality over Time*

	2006 Gini Coefficient	
	(1)	(2)
1980 Gini Coefficient	0.7934 [0.0734]**	0.6189 [0.0781]**
Ln(1980 Population)	0.0049 [0.0014]**	0.0037 [0.0014]**
Ln(1980 Median Family Income)	0.0293 [0.0126]*	0.0359 [0.0143]*
1980 Pct. Of 25+ Pop. With BA		0.1773 [0.0371]**
1980 Pct. Of 25+ Pop. With HS		-0.1366 [0.0246]**
Constant	-0.2165 [0.1367]	-0.1352 [0.1508]
Observations	242	242
R-squared	0.42	0.49

Notes:

Standard errors in brackets. * significant at 5%; ** significant at 1%

Source: The Gini coefficient for 2006 is from the American Community Survey, 2006. The Gini coefficient for 1980 is calculated using the 5% Integrated Public Use Microdata Series (IPUMS) for 1980, at usa.ipums.org. Other 1980 variables are from the 1980 Census.

Table 4
Consequences of Urban Inequality

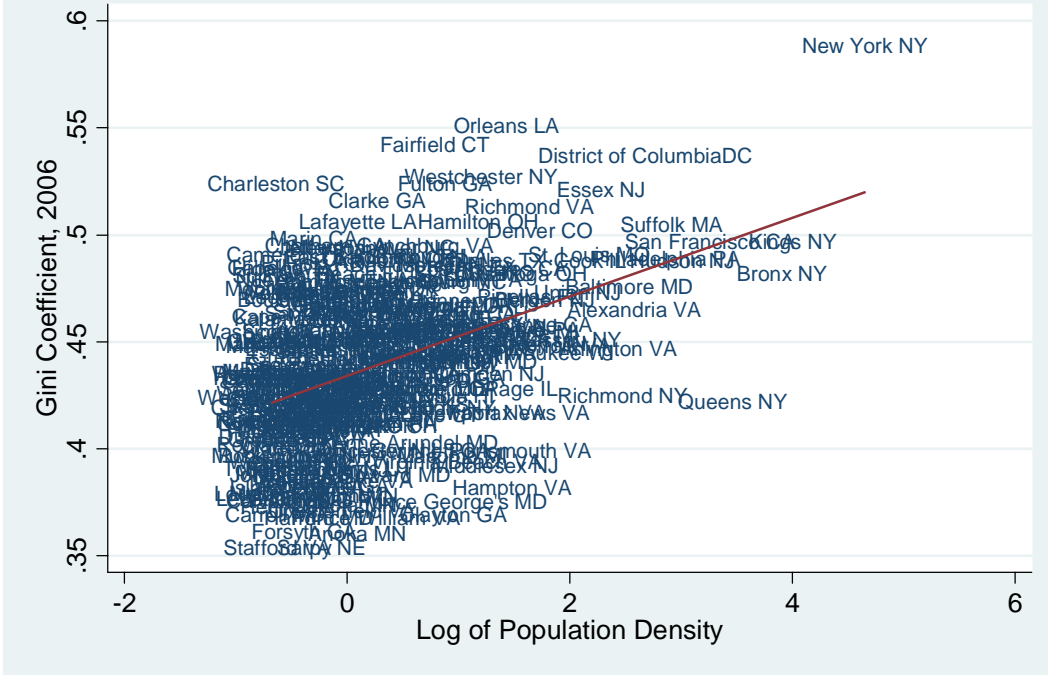
	Population Growth 1980-2000		Income Growth 1980-2000		Murder Rate per 100,000	
	(1)	(2)	(3)	(4)	(5)	(6)
1980 Gini Coefficient	1.0301 [0.7147]	-2.0335 [0.6512]**	-0.264 [0.3524]	-1.3893 [0.3635]**	50.3572 [14.5159]**	55.3637 [17.1951]**
Ln(1980 Population)	0.0329 [0.0141]*	0.017 [0.0112]	0.0255 [0.0069]**	0.0275 [0.0062]**	1.1389 [0.3450]**	0.9193 [0.3282]**
Ln(1980 Median Family Income)	-0.2484 [0.1228]*	-0.6385 [0.1141]**	-0.1137 [0.0606]	-0.4195 [0.0637]**	0.8419 [2.6157]	8.9701 [2.9379]**
1980 Pct. Of 25+ Pop. With BA		1.0094 [0.2995]**		1.2358 [0.1671]**		-12.388 [7.1261]
1980 Pct. Of 25+ Pop. With HS		0.8556 [0.1957]**		-0.0066 [0.1092]		-9.5897 [4.9076]
1994 Mean Jan. Temp.		0.0084 [0.0009]**		-0.0003 [0.0005]		0.0316 [0.0269]
Constant	1.8515 [1.3318]	6.0646 [1.1903]**	1.814 [0.6567]**	5.0625 [0.6644]**	-36.9898 [29.0251]	-109.0205 [31.1609]**
Observations	258	258	258	258	120	120
R-squared	0.05	0.4	0.04	0.18	0.2	0.29

Notes:

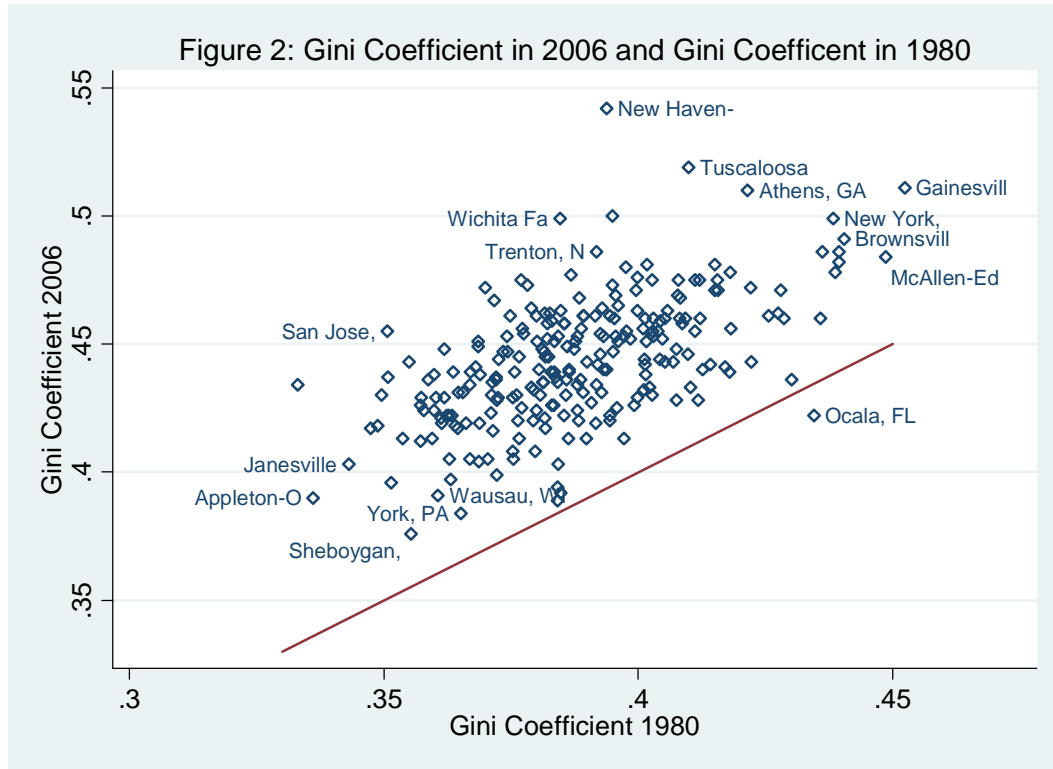
Standard errors in brackets. * significant at 5%; ** significant at 1%

Source: The Gini coefficient for 1980 is calculated using the 5% Integrated Public Use Microdata Series (IPUMS) for 1980, at usa.ipums.org. Other 1980 variables are from the 1980 Census. January temperatures are from the 1994 County and City Data Book from the U.S. Census.

Figure 1: Relationship Between the Gini Coefficient and Log Population Density, 2006



Source: 2006 American Community Survey

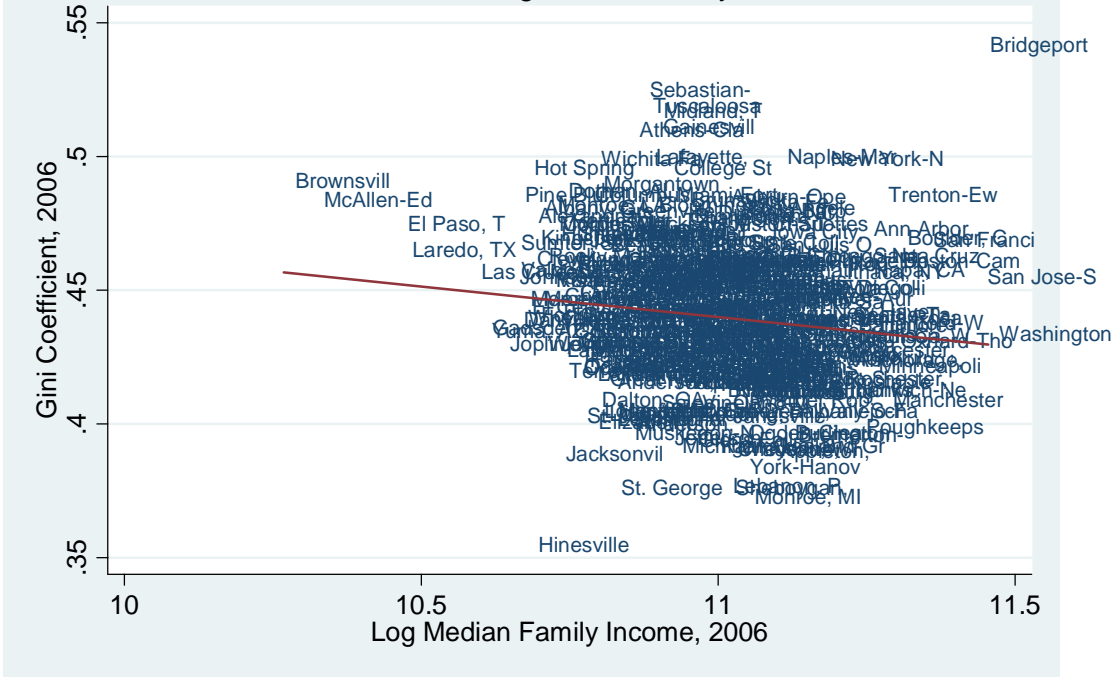


Notes: The line shown is the forty five degree line, *not* a fitted regression. Only some datapoints are labeled with their MSA names to aid readability.

Source: 1980 Gini coefficients are calculated from the 5% Integrated Public Use Microdata Series (IPUMS) for 1980, at usa.ipums.org. 2006 Gini coefficients are from the 2006 American Community Survey.

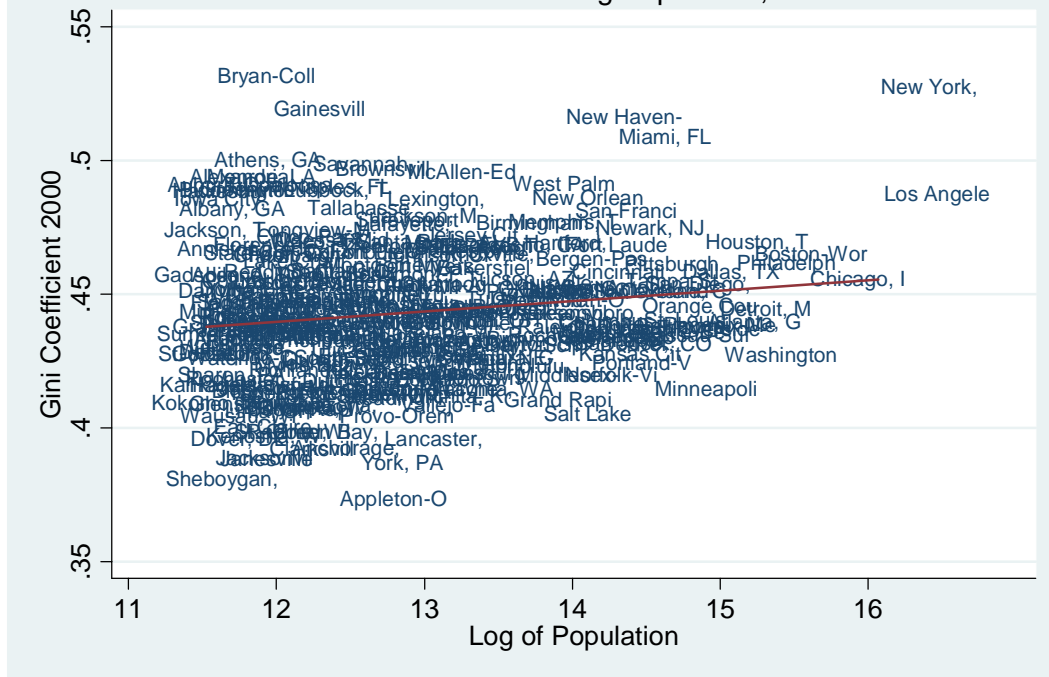
Source: 2006 American Community Survey

Figure 3: Relationship Between Gini Coefficient and Log Median Family Income, 2006

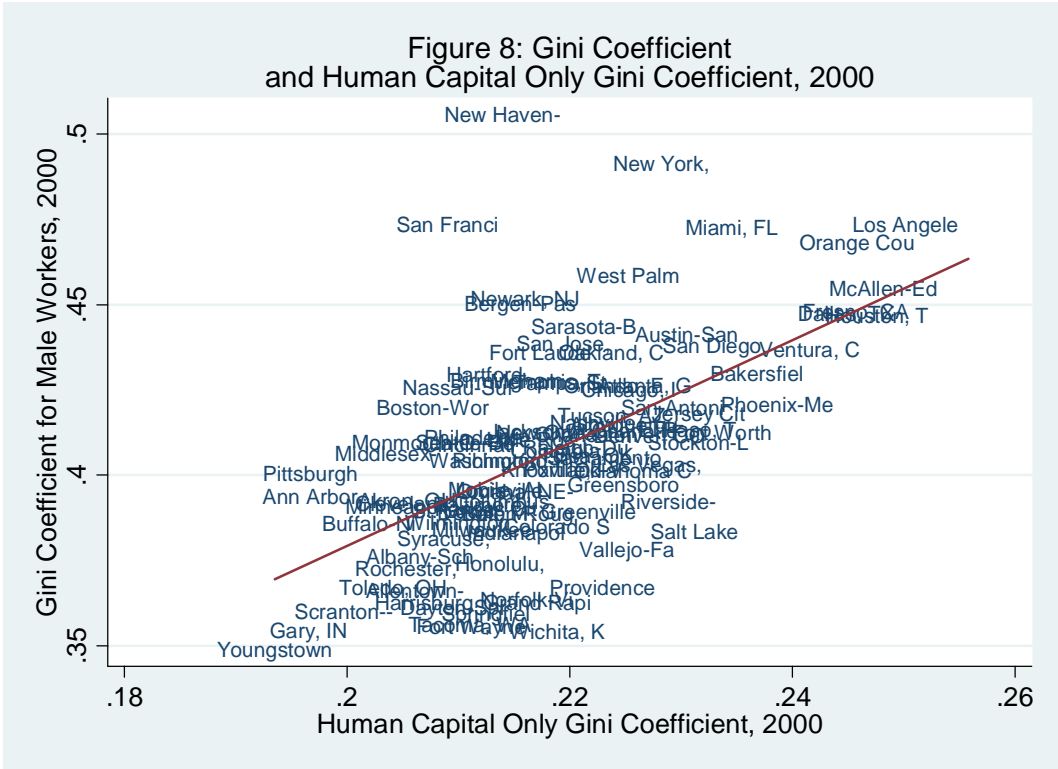


Source: 2006 American Community Survey

Figure 5: Relationship Between Gini Coefficient and Log Population, 2000

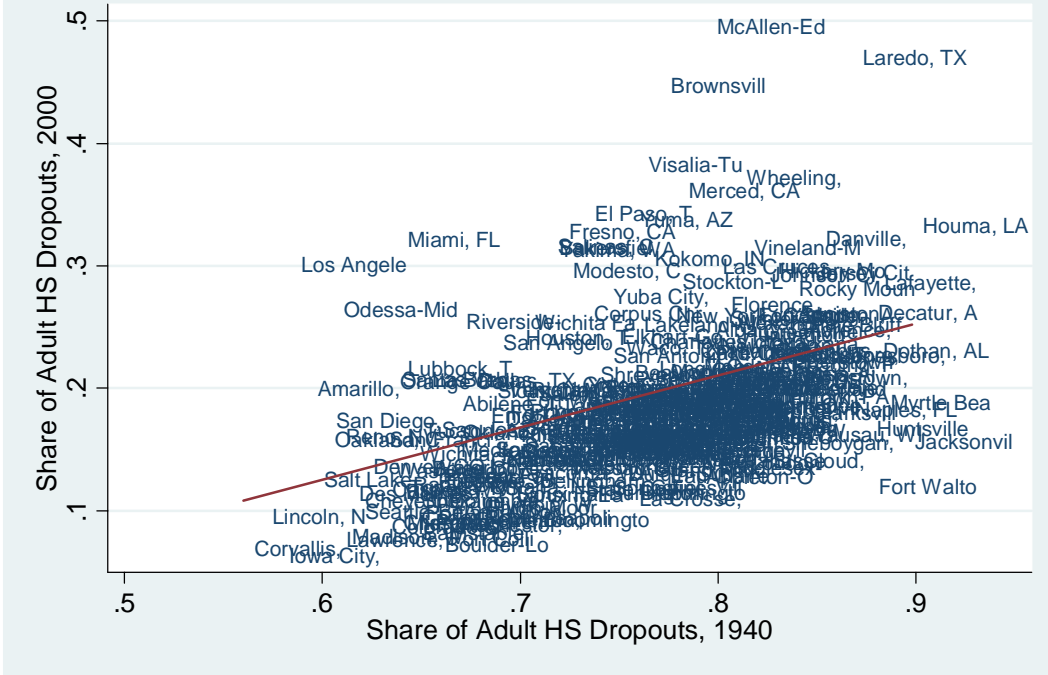


Source: Gini coefficients are calculated using the 5% Integrated Public Use Microdata Series (IPUMS) for 2000, at usa.ipums.org. Population data is from the 2000 Census.



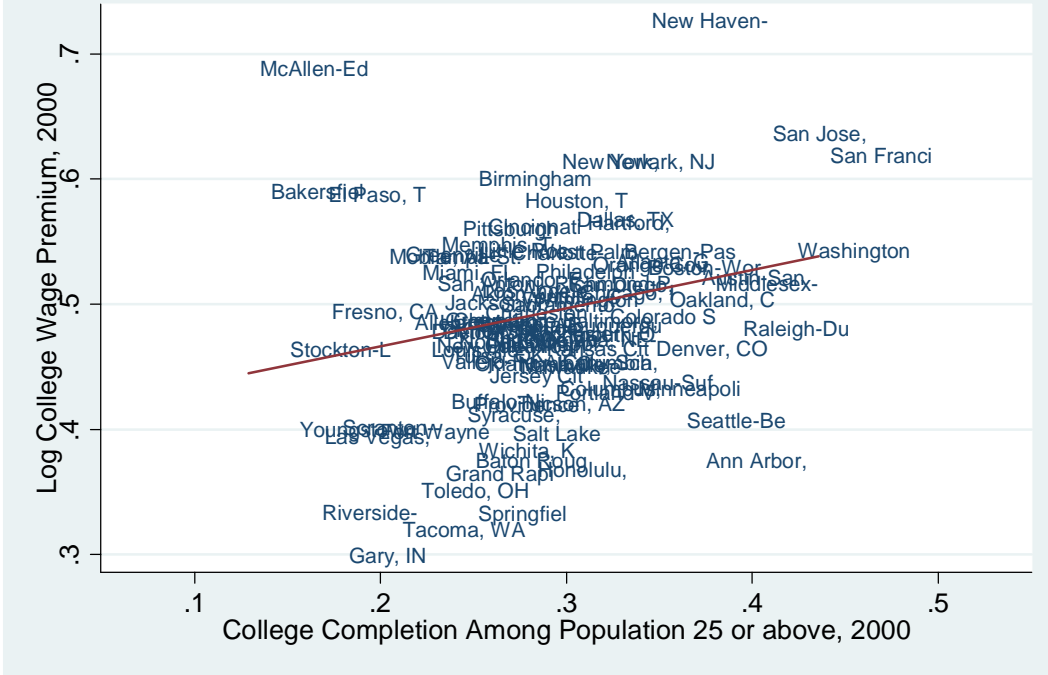
Source: Gini coefficients are calculated using the 5% Integrated Public Use Microdata Series (IPUMS) for 2000, at usa.ipums.org.

Figure 11: Relationship Between Share of Adult HS Dropouts, 2000 and Share of Adult HS Dropouts, 1940

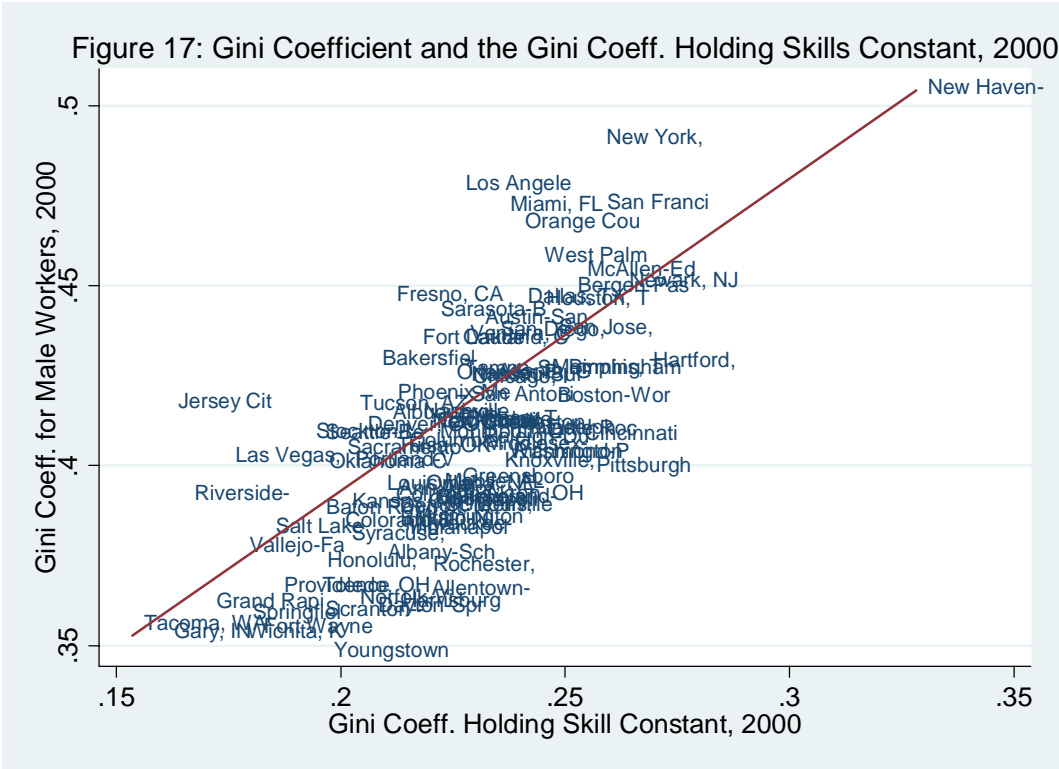


Source: Share of adult high school dropouts in 2000 is from the 2000 Census, and share of adult high school dropouts in 1940 is from Haines, M.R., ICPSR study number 2896. Historical, Demographic, Economic, and Social Data: The United States, 1790-2000.

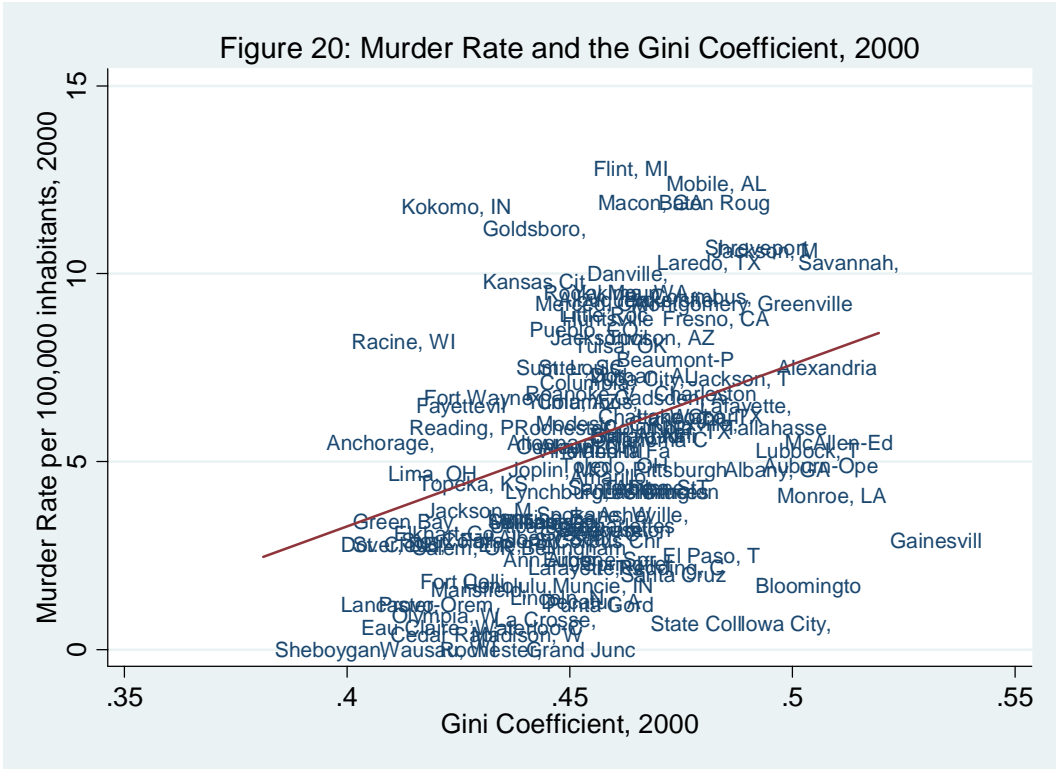
Figure 15:
Returns to College and the Percent of Residents with College Degree, 2000



Source: Data is calculated using the 5% Integrated Public Use Microdata Series (IPUMS) for 2000, at usa.ipums.org.



Source: Gini coefficients are calculated using the 5% Integrated Public Use Microdata Series (IPUMS) for 2000, at usa.ipums.org.



Source: Gini coefficients are calculated using the 5% Integrated Public Use Microdata Series (IPUMS) for 2000, at usa.ipums.org. Murder rates are from the FBI's Uniform Crime Reports.

