

INEQUALITY IN CITIES*

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ABSTRACT. Much of the inequality literature has focused on national inequality, but local inequality is also important. Crime rates are higher in more unequal cities; people in unequal cities are more likely to say that they are unhappy. There is a negative association between local inequality and the growth of city-level income and population, once we control for the initial distribution of skills. High levels of mobility across cities mean that city-level inequality should not be studied with the same analytical tools used to understand national inequality, and policy approaches need to reflect the urban context. Urban inequality reflects the choices of more and less skilled people to live together in particular areas. City-level skill inequality can explain about one-third of the variation in city-level income inequality, while skill inequality is itself explained by historical schooling patterns and immigration. Local income also reflects the substantial differences in the returns to skill across, which are related to local industrial patterns.

1. INTRODUCTION

The inequality of cities may be as important as the inequality of countries. The connection between crime and inequality is as strong within urban areas as it is across countries (Daly, Wilson, and Vasdev, 2001; Fajnzylber, Lederman, and Loayza, 2002). Envy is more likely to be directed toward near neighbors, than geographically dispersed compatriots (Luttmer, 2005). Inequality within cities seems as likely to generate political uprisings as inequality across large geographic units. Yet almost all of the economic research on inequality has focused on countries rather than cities.

Moreover, there are many reasons to think that inequality within cities is quite different than inequality within countries. The ready movement of

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people across space within a nation means that the inequality of a particular place is likely to reflect the selection of skilled and unskilled workers into that place. Easy mobility across city boundaries means that redistributive policies that would lead to a more equal society if applied at the national level may lead to disastrous results at the city level. City-specific redistribution may lead to an exodus of the wealthy and an influx of the poor that leaves the city impoverished.

In this paper, we look at the causes and consequences of urban inequality. America is, on the whole, relatively unequal for a developed country (Alesina and Glaeser, 2004), but there are some areas within the United States that are a lot more equal than others. While Manhattan is the physical embodiment of big-city inequality and has a Gini coefficient of 0.6, 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 in 2006, and 9.3 percent of households earned less than \$25,000. In contrast, 20.4 percent of households in New York County earned more than \$150,000, and 26.5 percent earned less than \$25,000. In Section 2 of this paper, we discuss the measurement of inequality across metropolitan areas.

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 3, we find that almost one-third 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. One-half of the variation in income inequality can be explained by the occupation-based inequality. 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 accept 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 in the 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 that 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 4 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. Our data also confirm 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 5, 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. Local redistribution may just increase that segregation. Section 6 concludes.

2. 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 multicounty 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.

We have chosen to use Primary, rather than Consolidated, metropolitan areas, which are somewhat smaller units. This decision allows us to work with more observations, and it picks up variation within massive agglomerations, but it also creates some mismeasurement because occasionally, the residents of one area work in another.

Much of the data for this paper come from the 5 percent integrated public-use micro-samples (IPUMS) for the 1980 and 2000 Censuses (Ruggles et al., 2008). In most cases, we restrict ourselves to total household income, which means that we are not treating single people differently from married people. We focus on pretax 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 and at \$75,000 in 1980. 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 is 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° 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 10 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, 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 5 percent microsample, 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

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

²If 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., $\frac{1}{\hat{y}} \int_{y \leq F^{-1}(p)} f(y)y dy$.

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 have a fairly high correlation. For example, the correlation coefficient between the Gini coefficient and the coefficient of variation is 92 percent. The correlation 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 United States 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. Overall, the correlation between the Gini coefficient in 1980 and the Gini coefficient in 2006 is 0.58, 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 0.1, the growth in the Gini coefficient over the next 26 years falls by 0.03. Some of the impermanence (and mean reversion) surely reflects measurement error in the Gini coefficient.

In 1980, the Gini coefficients ranged from 0.33 to 0.45. Wisconsin had the most equal metropolitan areas 25 years ago with the Appleton-Oshkosh-Neenah MSA's Gini coefficient of 0.33, and Gainesville, Florida, was the most unequal metropolitan area with a Gini coefficient of 0.45. 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 0.38), 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 0.54.

While the counties of New York (Manhattan), Fairfield, Connecticut, and Orleans Parish, Louisiana, when taken by themselves have higher Gini coefficients than the New Haven-Bridgeport-Stamford metropolitan statistical area, 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.

The inequality of the New Haven-Bridgeport-Stamford metropolitan statistical area, and its wealth, reflects its place as a part of the extremely productive greater New York area. This area has attracted some of the wealthiest workers in the region, some of whom continue to work in Manhattan,

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 percent Integrated Public Use Microdata Series (IPUMS) for 2000, at usa.ipums.org. Median family income and population are from the 2000 Census.

and some of whom now work in Greenwich or other suburban areas. The area also contains some older industrial areas that remain extremely poor.

In 1980, there was a strong -59 percent correlation coefficient between metropolitan area income and inequality. Today, the correlation coefficient is -14 percent. Twenty-five years ago, inequality was strongly associated with poverty. Today, the correlation is much weaker because there has been an explosion of earnings among the richest Americans, which has made wealthy places more unequal as well. 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 (-0.02). In 2000, the Gini coefficient has a 15 percent correlation with area population. 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.

In 2000, the most equal Census divisions were the Great Plains and the Midwest (Gini coefficient averages of 0.428 and 0.427, respectively) and the least equal divisions were the South and the New England (Gini coefficient averages of 0.457 and 0.46, respectively). These cross-division differences seemed relatively small, not particularly stable and not particularly permanent over time. For these reasons, we directed our focus on more local variables, such as the distribution of skills, rather than more regional variables, such as market potential.

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 Broda and Romalis (2008), 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

TABLE 2: Causes of Urban Inequality

	1980 Gini		2000 Gini				
	(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]	

Continued

TABLE 2: Continued

	2000 Gini Coefficient						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1850 illiteracy rate						0.061	
1850 pct. of pop. enslaved						[0.0327]	
Share of labor force in manufacturing, 1950						0.0372	
Constant						[0.0102]**	-0.0447
							[0.0109]**
							0.9174
							[0.0960]**
Observations	1.3835	1.013	1.5937	1.1751	0.9877	0.7564	
R^2	[0.0782]**	[0.0960]**	[0.1045]**	[0.0917]**	[0.1311]**	[0.1411]**	
	258	282	282	281	208	208	281
	0.39	0.15	0.49	0.32	0.2	0.26	0.19

Notes: Standard errors in brackets. *Significant at 5 percent, **significant at 1 percent.

Source: The Gini coefficients are calculated using the 5 percent 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.

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 United States. 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 through 2004.³ 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.

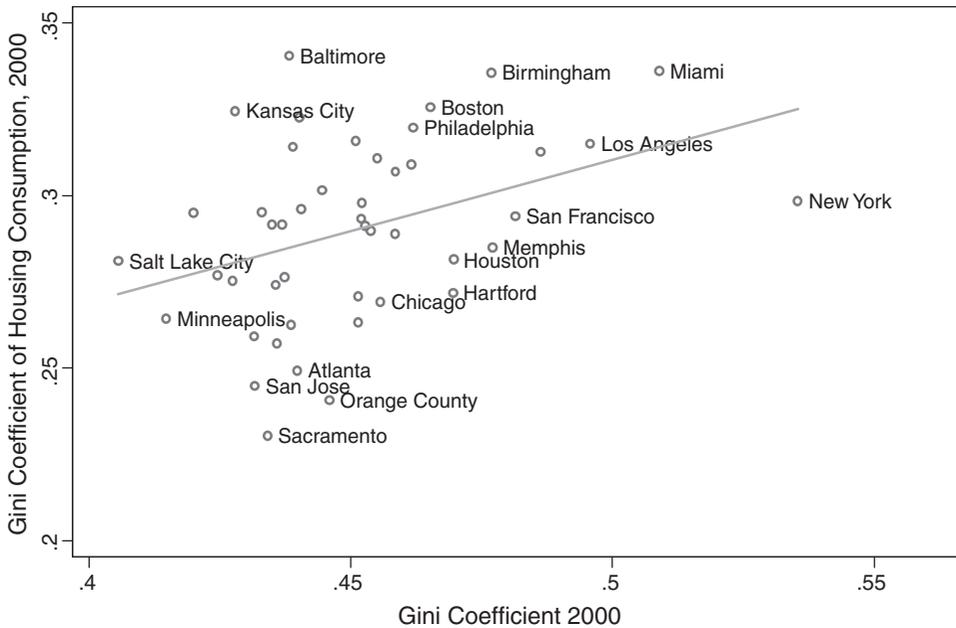
We use this housing consumption measure to calculate a Gini coefficient of housing consumption for every metropolitan area. Figure 1 shows the 38 percent correlation between this housing consumption Gini coefficient and our income Gini coefficient. More unequal incomes also have more unequal housing 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 0.29, 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.

3. 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

³Data from 1998, 1999, 2002, 2003, and 2004 is used. There was no metropolitan supplement in 2000 or 2001.



Source: The 2000 Gini coefficient is calculated using the 5 percent Integrated Public Use Micro-data Series (IPUMS) for 2000, at usa.ipums.org. The housing Gini coefficient was calculated using housing values and controls from the American Housing Survey Metropolitan Samples for 1998, 1999, 2002, 2003, and 2004. There was no metropolitan supplement in 2000 or 2001.

FIGURE 1: Gini Coefficient of Housing Consumption and the Gini Coefficient, 2000.

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 $[\hat{h}_i - 0.5\sigma_i, \hat{h}_i + 0.5\sigma_i]$ 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^2) 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 0.031, a little more than one standard deviation. As the share of high school graduates increases by 10 percent, the Gini coefficient drops by 0.018, about two-thirds of a standard deviation. While it may be surprising 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^2 declines to 32 percent, but these historical variables incrementally explain more than 15 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.⁴ The coefficients on these enrollment rates are not, therefore, particularly comparable with the coefficients on population-based skill measures in regressions (3) and (4). Unfortunately, we also lose over 70 metropolitan areas by using this historical data. Nonetheless, 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^2 created by those two variables when compared to regression (2) is quite modest (5 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. Slave owners 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 these variables increases the R^2 of the regression to 26 percent, an additional 6 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, calculated using the American Community Survey (ACS), on the Gini coefficient in the year 1980 and other controls. Though the ACS has a smaller sample size than the full 2000 Census, we use the 2006 measure here because it increases the time

⁴Haines (2004) ICPSR study number #2,896, 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^2	0.42	0.49

Notes: Standard errors in brackets. *Significant at 5 percent, **significant at 1 percent.

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

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 0.79 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 coefficients 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, and there is a 74 percent correlation between this Gini coefficient and our household income Gini coefficient among these 102 metropolitan areas.

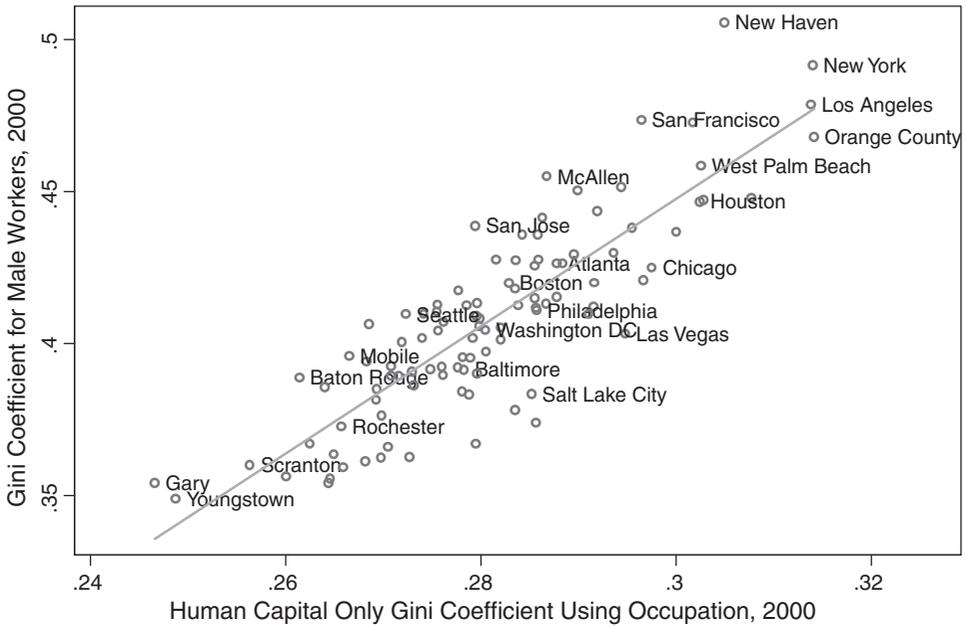
We then compare this Gini coefficient for male workers with Gini coefficients based entirely on the human capital of these workers, by which we mean age and years of schooling. To calculate these “human capital only” Gini coefficients, we use a nationwide earning regression to predict earnings for everyone 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, and there is 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 toward explaining the amount of income inequality.⁵

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 toward explaining income inequality across areas.

Figure 2 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.

⁵This work parallels the work of Combes, Duranton, and Gobillon (2008) on sorting by skill across French areas. Like them, we find that sorting by skill matters, but in our case, we are focused on the distribution of earnings within area, rather than the mean earnings of an area.



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

FIGURE 2: Gini Coefficient and Human Capital Only Gini Coeff. Using Occupations, 2000.

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 economists who emphasize people's location decisions will tend to focus on differences in economic productivity and differences in amenities that motivate migration (e.g., Dahl, 2002). According to this view, areas that specialize in industries that are particularly good for low- or high-skill workers should 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.

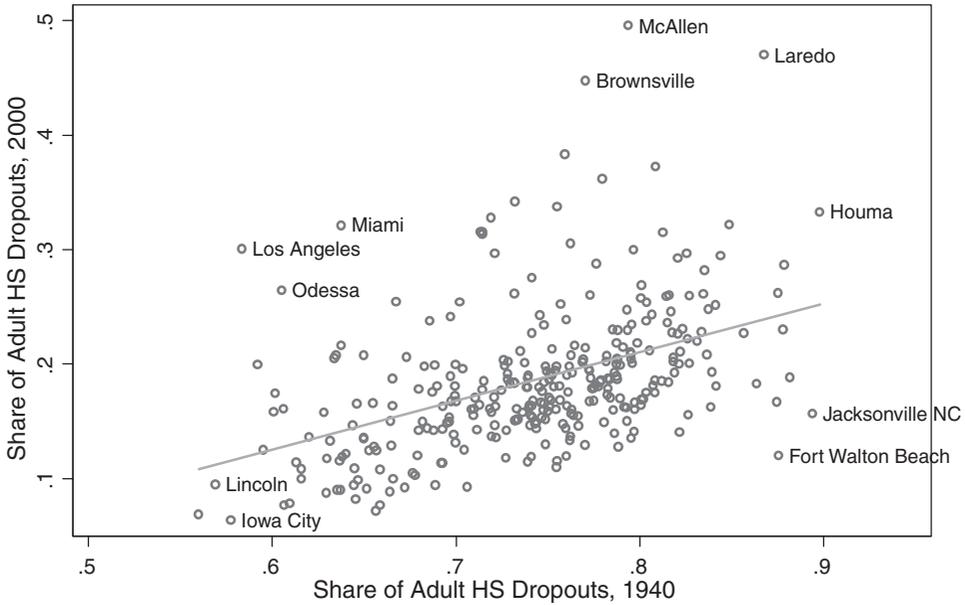
While the economic framework that emphasizes rational location choice certainly has some ability to explain the distribution of skilled people across space, many of the current skill patterns appear to be determined by long-standing historical skill patterns, as discussed above. For example, there is a 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. There is a 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. Figure 3 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 percentage 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. There is a 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. The correlation between Hispanic share and MSAs latitude is -36 percent, reinforcing 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 no robust association between January temperature and the share of the population with college degrees.



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 3: Relationship Between Share of Adult HS Dropouts, 2000 and Share of Adult HS Dropouts, 1940.

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 would 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.

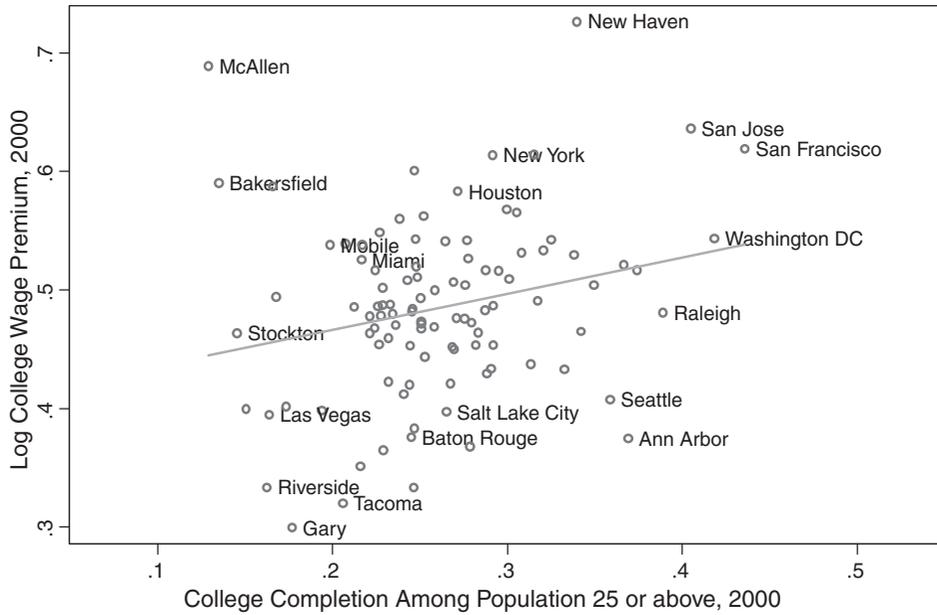
There is a 79 percent correlation between this measure of high-skilled industries and the share of the population with college degrees, and a 49 percent correlation between the share of the adult population without a college degree and the measure of low-skill industries. Certainly, there is a robust 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 7 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 toward 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

$$(1) \text{Log}(Wage) = \alpha_{MSA} + \beta_{MSA}^{BA} * BAGrad + \beta_{MSA}^{HS} * HSGrad + \text{OtherControls},$$



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

FIGURE 4: Returns to College and the Percentage of Residents with College Degree, 2000.

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. As we control for a metropolitan area-fixed effect, we do not also control for area-level controls, not do we interact any area-level characteristics with the education variables, since we are estimating a distinct return to education for each metropolitan area. In a second stage, we will then correlate these estimated coefficients with area-level controls, such as education and density. We focus only on those areas with more than 500,000 people so that the returns to schooling are estimated with reasonable precision.

Figure 4 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.⁶ One interpretation of this fact is that skilled people are moving to places where the skill levels are

⁶We also examined the correlation between this estimated coefficient and the logarithm of area density. We found that the coefficient was slightly stronger in dense areas, but that controlling

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

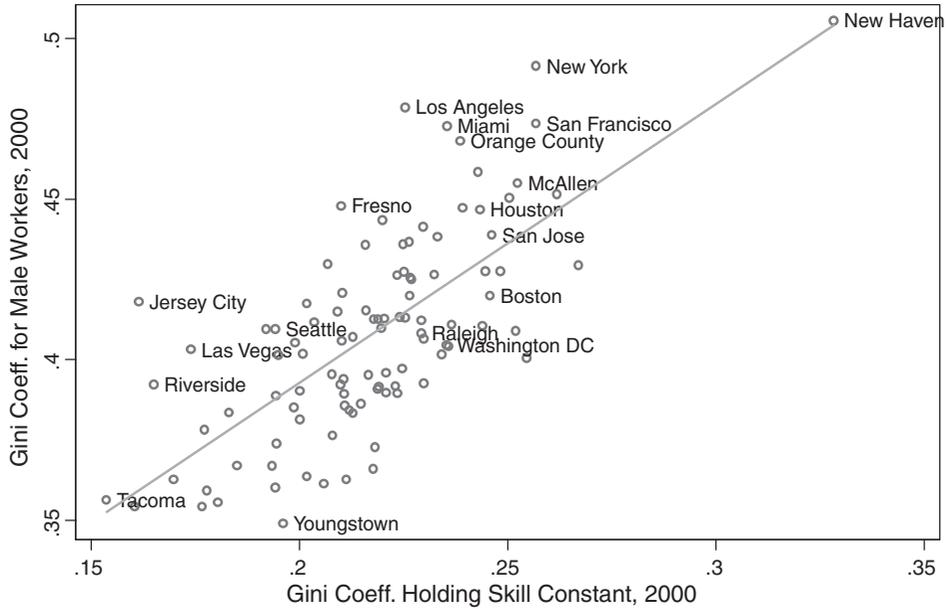
The fact that the returns to human capital differ across space can also potentially explain the inequality that we see across metropolitan areas. As the formula discussed above illustrates, pretax income inequality will reflect both differences in the distribution of skills and differences in the returns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

There is a 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 are 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 5 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

for density did little to the estimated relationship between this coefficient and the share of the population with college degrees.



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

FIGURE 5: Gini Coefficient and the Gini Coefficient Holding Skills Constant, 2000.

better than differences in measured human capital. As in Combes, Duranton, and Gobillon (2008), “sorting matters,” but so do differences in the returns to skill.

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 does not explain the returns to skills. 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.⁷

We calculate a 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.⁸ There is a 27 percent correlation between the returns to college and the share of workers in the computer industry among the same sample of cities, again lending support to the results of Beaudry et al. (2006) show a link between computerization and inequality.⁹ 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 et al. (2006) have brought some understanding to this question, but it remains a pressing topic for future research.

⁷Like Black, Kolesnikova, and Taylor (2007), we find a modest positive relationship between cost of living and returns to college.

⁸“Finance” is defined using IPUMS 2000 Occupation Codes for the 5 percent sample at <http://usa.ipums.org/usa/volii/00occup.shtml>. Finance codes are 12, and 80–95.

⁹“Computers” is also defined using IPUMS 2000 Occupation Codes for the 5 percent sample at <http://usa.ipums.org/usa/volii/00occup.shtml>. Computer codes are 11, 100–111, and 140.

4. 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 (Alesina and Rodrik, 1994; Persson and Tabellini, 1994). However, 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 outmigration.

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, 2000). Egalitarians can simultaneously hope for policies that would reduce inequality at the national level, such as increasing the schooling levels for the 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 moving to an area.

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 0.45, would cause population growth to fall by about 1 standard deviation.

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 ²	0.05	0.4	0.04	0.18	0.2	0.29			

Notes: Standard errors in brackets. * Significant at 5 percent, ** significant at 1 percent.

Source: The Gini coefficient for 1980 is calculated using the 5 percent 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.

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 et al., 2002). These results have also been found at the metropolitan area level (Daly et al., 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. There is a 35 percent correlation between homicide rates and the Gini coefficient across metropolitan areas. 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.¹⁰ Luttmer's evidence suggests the importance of thinking about inequality at the local level.

We find a -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.

¹⁰We 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.

5. POLICIES TOWARD INEQUALITY AT THE LOCAL AND NATIONAL LEVEL

While the primary theme of this paper is that inequality should be studied at the local as well as at the national level, there are good reasons to think that national governments are better suited toward addressing the problems of inequality than local governments. 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.

Inequality differs greatly across nations and much of that heterogeneity has been associated with different national policies (Glaeser, 2005). For example, many European countries have set up welfare states that engage in much more redistribution than the United States (Alesina and Glaeser, 2004). If the national government takes money from the rich and gives it to the poor, then inequality will fall. The costs of such policies, reduced effort and savings and innovation, may make redistribution unattractive, but there is no question that nations are capable of significantly reducing inequality.

Localities, however, face a far more mobile tax base. When a city raises the local tax rate in order to pay for a local welfare state, then the rich can flee. Generous welfare payments will attract the poor. At the extreme, attempts by cities to run local welfare states can actually reduce the local resources available to the poor by increasing the segregation of rich and poor. Of course, mobility is not perfect and places do manage to redistribute something locally, yet their ability to engage in redistribution is certainly limited by free migration across cities.

Many economics papers have documented that the poor move in response to generous local welfare policies. Borjas (1999) shows that more generous welfare policies across states attracted less skilled immigrants, especially to California. Blank (1988) finds that generous welfare payments impact the location decision of unmarried women with children. East St. Louis, which is within the St. Louis metropolitan area, but which sits on the more generous Illinois side of the Mississippi river is something of a natural experiment. The city has long been one of the poorest areas in the United States, which illustrates the ability of generous welfare payments to attract the poor.

There is also evidence that the rich respond to local tax rates and public goods that cater to their own interests. In many American metropolitan areas, the rich have fled central cities and moved to suburbs that have less redistribution and better schools. Haughwout et al. (2004) argue that cities can actually lose revenue by raising taxes because the rich find it so easy to emigrate. Similarly, Feldstein and Wrobel (1998) find that states cannot effectively redistribute income at all because of the mobility of the rich.

This evidence does not imply that localities can not reduce inequality, but instead that localities cannot reduce inequality by redistributing income. Localities can reduce income inequality by inducing the rich to leave. This can result in a more homogenous community, albeit one that is much poorer. Of

course, few places would actually want to increase equality by driving away their richest taxpayers. This emigration could in fact hurt the poorest people in the city by reducing employment opportunities.

Localities can also impact redistribution through education policy. However, some investments in education may well increase local inequality. When we regress the area Gini coefficient on Moretti's (2004) land-grant college variable, we find that inequality is higher in places with a land-grant college, controlling for area population, income, and the share of adults who are high school dropouts. 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.

Presumably, reducing local inequality requires investing disproportionately in schools that cater to the less fortunate. 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.

While it might be beneficial to reduce inequality by improving the education of the less fortunate, local governments have again only a limited ability to make the nationwide skill distribution more equal. Areas with many poor parents have fewer resources with which to educate their children. These places not only 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.

Finally, 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, if national inequality were kept constant. 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.

6. CONCLUSION

The bulk of the research on inequality has focused on inequality at the nation level. Yet most people live in cities and their experience of inequality is shaped by their local environment. This fact implies the need to research inequality in cities as well as inequality in countries.

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 toward 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. Though the raw correlation between area-level inequality and population growth is positive, more unequal places grow more slowly once we control for the skill distribution in an area.

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 toward a focus on policies like human capital development that would promote equality nationwide.

REFERENCES

- Alesina, A. and E.L. Glaeser. 2004. *Fighting Poverty in the U.S. and Europe: A World of Difference*. New York: Oxford University Press.
- Alesina, A. and D. Rodrik. 1994. "Distributive Politics and Economic Growth," *Quarterly Journal of Economics*, 109(2), 465–490.
- Autor, D. and D. Dorn. 2007. "Inequality and Specialization: The Growth of Low-Skill Service Jobs in the United States," MIT mimeograph.
- Beaudry, P., M.E. Doms, and E.G. Lewis. 2006. "Endogenous Skill Bias in Technology Adoption: City-Level Evidence from the IT Revolution," NBER Working Paper.
- Berry, C. and E.L. Glaeser. 2005. "The Divergence of Human Capital Levels Across Cities," *Papers in Regional Science*, 84(3), 407–444.
- Black, D., N. Kolesnikova, and L.J. Taylor. 2007. "Earnings Functions When Wages and Prices Vary by Location," Working Papers. Federal Reserve Bank of St. Louis.
- 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.
- Broda, C. and J. Romalis. 2008. "Inequality and Prices: Does China Benefit the Poor in America?," mimeo, University of Chicago GSB.
- Brueckner, J.K., J.-F. Thisse, and Y. Zenou. 1999. "Why is central Paris Rich and Downtown Detroit Poor? An Amenity-Based Theory," *European Economic Review*, 43, 91–107.
- Combes, P.-P., G. Duranton, and L. Gobillon. 2008. "Spatial Wage Disparities: Sorting Matters!" *Journal of Urban Economics*, 63(2), 723–742.
- Cutler, D., E.L. Glaeser, and J. Vigdor. 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., M. Wilson, and S. Vasdev. 2001. "Income Inequality and Homicide Rates in Canada and the United States," *Canadian Journal of Criminology*, 43(2), 219–236.
- Ellison, G. and E.L. Glaeser. 1999. "The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration?" *American Economic Review Papers and Proceedings*, 89(2), 311–316.
- Fajnzylber, P., D. Lederman, and N. Loayza. 2002. "Inequality and Violent Crime," *Journal of Law and Economics*, 45(1), 1–40.
- Feldstein, M. and M.V. Wrobel. 1998. "Can State Taxes Redistribute Income?" *Journal of Public Economics*, 68(3), 369–396.
- Glaeser, E.L. 2000. "The Future of Urban Research: Nonmarket Interactions," in William G. Gale and Janet Rothenberg Pack, eds., *Brookings-Wharton Papers on Urban Affairs 2000*. Washington, D.C.: Brookings Institution Press, 101–149.
- . 2005. "Inequality," NBER Working Paper #11511.
- Glaeser, E.L. and J.D. Gottlieb. 2008. "The Economics of Place-Making Policies," *Brookings Papers on Economic Activity*.
- Glaeser, E.L., M.E. Kahn, and J. Rappaport. 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, MA: Belknap Press.
- Haines, M.R. 2004. Historical, Demographic, Economic, and Social Data: The United States, 1790-2000, Inter-University Consortium for Political and Social Data. Available online at: <http://www.icpsr.umich.edu/cocoon/ICPSR/STUDY/02896.xml>.
- Haughwout, A., R. Inman, S. Craig, and T. Luce. 2004. "Local Revenue Hills: Evidence from Four U.S. Cities," *The Review of Economics and Statistics*, 86(2), 570–585.
- Katz, L. and K. Murphy. 1992. "Changes in Relative Wages, 1963-1987: Supply and Demand Factors," *Quarterly Journal of Economics*, 107(1), 35–78.
- LeRoy, S.F. and J. Sonstelie. 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. and G. Ragusa. 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, IL: University of Chicago Press.
- Persson, T. and G. Tabellini. 1994. "Is Inequality Harmful for Growth?" *American Economic Review*, 84(3), 600–621.
- Ruggles, S., M. Sobek, T. Alexander, C.A. Fitch, R. Goeken, P.K. Hall, M. King, and C. Ronnander. 2008. Integrated Public Use Microdata Series. Available online at: <http://usa.ipums.org/usa>.
- Wilson, W.J. 1987. *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy*. Chicago, IL: Chicago University Press.

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