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POLICY BRIEFS

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Urban Inequality

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Introduction

For 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. America is an unequal nation, and while there is certainly plenty of rural inequality, there is a 44 percent correlation between inequality and density across those U.S. counties with more than one person per every two acres. Moreover, just as inequality within the United States as a whole has been rising since the 1970s, inequality in almost every metropolitan area has risen since 1980. In many cases, the increase in inequality has been considerable.

This policy brief reviews the economic determinants of inequality at a local level. Pre-tax income inequality is generally understood as reflecting the distribution of skills in the population as well as the return to skill. Additionally, many of the most unequal places got that way by attracting particularly large numbers of less skilled immigrants, who are attracted to these areas because they provide economic opportunity and a socially comfortable milieu. The role that recent immigration plays in urban inequality reminds us that cities are, in part, unequal because they manage to attract both skilled and unskilled people, which is in many ways a reflection of urban strength.

There are good reasons to be concerned about high levels of inequality. Many value systems treat inequality as undesirable in and of itself, and research suggests that highly unequal society might be problematic, negatively affecting economic growth, happiness, and crime rates. Yet it isn't obvious that there are any good ways to reduce inequality at the city level. Increasing equality at the local level, while leaving national inequality untouched, requires the sorting of likes with likes. Segregation by income is another word for this kind of local equality, and there are many reasons to think that this type of segregation is to be avoided rather than pursued.

The Measurement of Inequality and Changes over Time

We use person-level data in our analysis, taken from the five-percent 1980 and 2000 Census Integrated Public-Use Micro-Samples (IPUMS) (Ruggles et al, 2008). We use total pre-tax household income as our measure of income. The standard measure of

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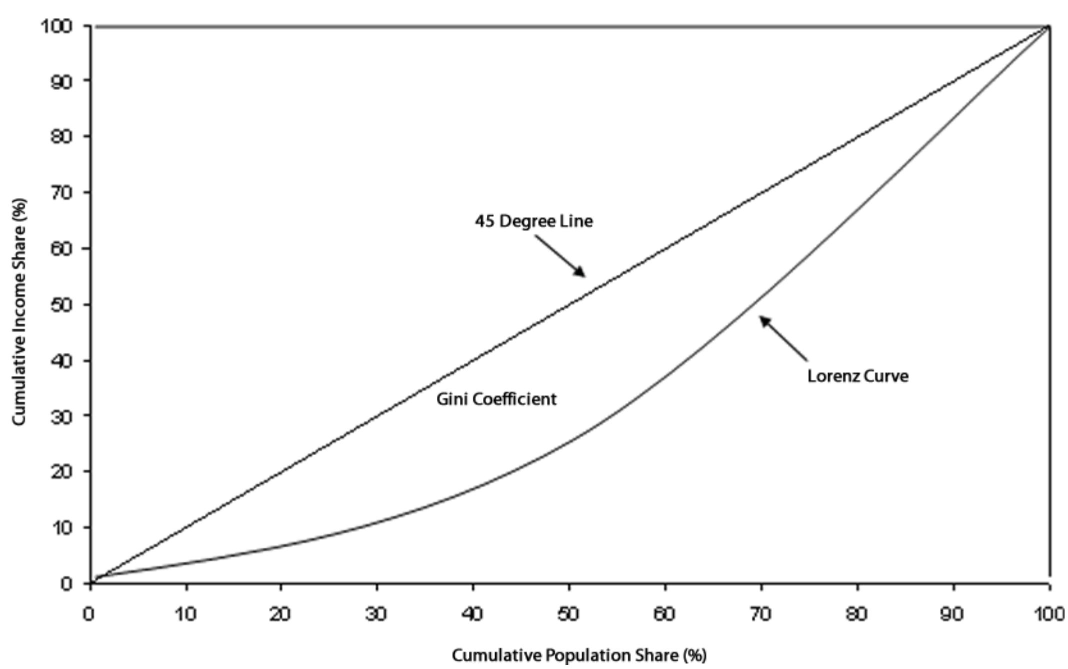
income inequality is the Gini coefficient, which is represented graphically in Figure 1. The Gini coefficient is the area between the 45 degree line (which indicates perfectly equal, income distribution) and the Lorenz curve (which represents the actual income distribution), and ranges from zero (perfect equality) to one (all income is in the hands of one household). There are other attractive measures of inequality, but since we found that these measures are quite correlated with the Gini coefficient, we stick to the "industry standard."

We calculate Gini coefficients for 242 metropolitan areas in 1980 and a somewhat larger sample of metropolitan areas in 2000. 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. In every metropolitan area, except for Ocala, Florida, the Gini coefficient is higher today than it was 26 years ago.

The nature of urban inequality does seem to have changed somewhat over the last 26 years. While in 1980, inequality was driven by the poorest Americans, today inequality is also driven by the number of very rich Americans. Because the rich have gotten so much richer over the past 25 years, the ability of the rich to drive local inequality figures has also become greater. This very fact, though, should perhaps make public officials cautious about trying to reduce inequality at the local level. Inequality could be reduced if wealthier Americans were to leave the area, but advocating policies that might induce an area's highest earning, and highest tax paying citizens, to leave does not sound like a recipe for urban success.

However, 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.

Figure 1: Gini Coefficient

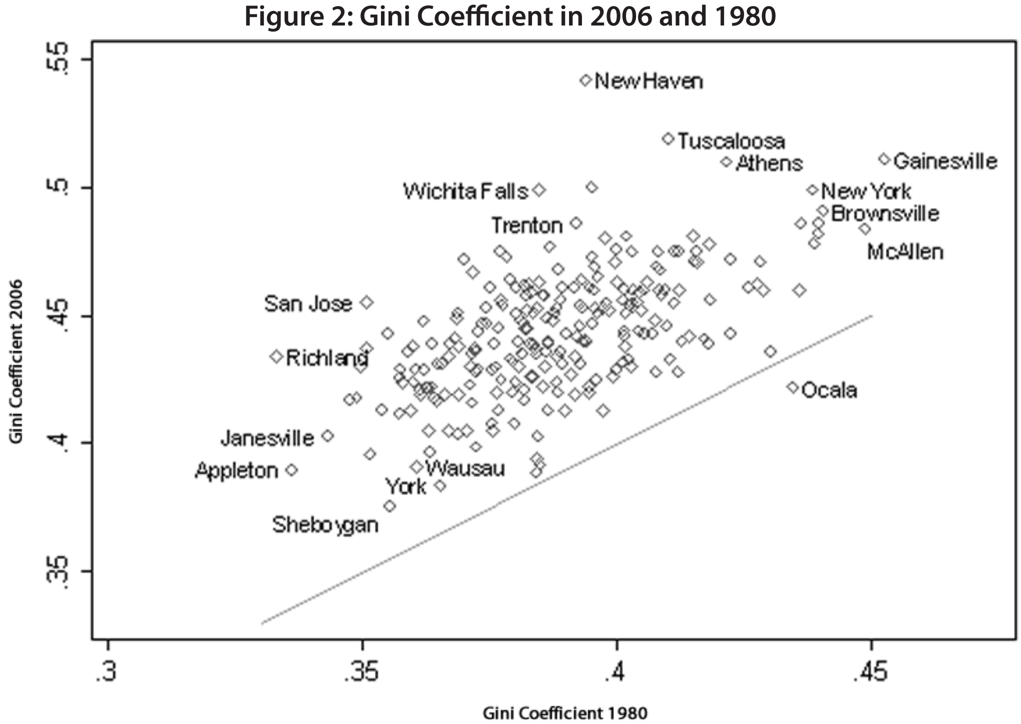


However, as suggested by Broda and Romalis (2008), prices may be quite different for people at different places in the income distribution. New York may be much more expensive for a relatively rich person than it is for a relatively poor person.

Enrico Moretti (2008) has addressed this by developing different price indices for people at different levels of the income distribution in different metropolitan areas, and we do not attempt to replicate his excellent results. 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, by using data for 46 of the largest metropolitan areas from the American Housing Survey Metropolitan Samples for 1998 through 2004 and forming a predicted housing price measure for every household. We use this housing consumption measure to calculate a Gini coefficient of housing consumption for every metropolitan area. 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. 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. Though fact does not prove that prices are largely offsetting incomes, it suggests that places with highly unequal income levels have less housing consumption inequality than one might expect.

Figure 2: Gini Coefficient in 2006 and 1980



Notes: The line shown is the forty-five degree line, not a fitted regression. Only some datapoints are labled with their MSA names to aid readability.
Source: 1980 Gini coefficients are calculated from the 5 percent Integrated Public Use Microdata Series (IPUMS) for 1980, at usa.ipums.org. 2006 Gini coefficients are from the 2006 American Community Survey.

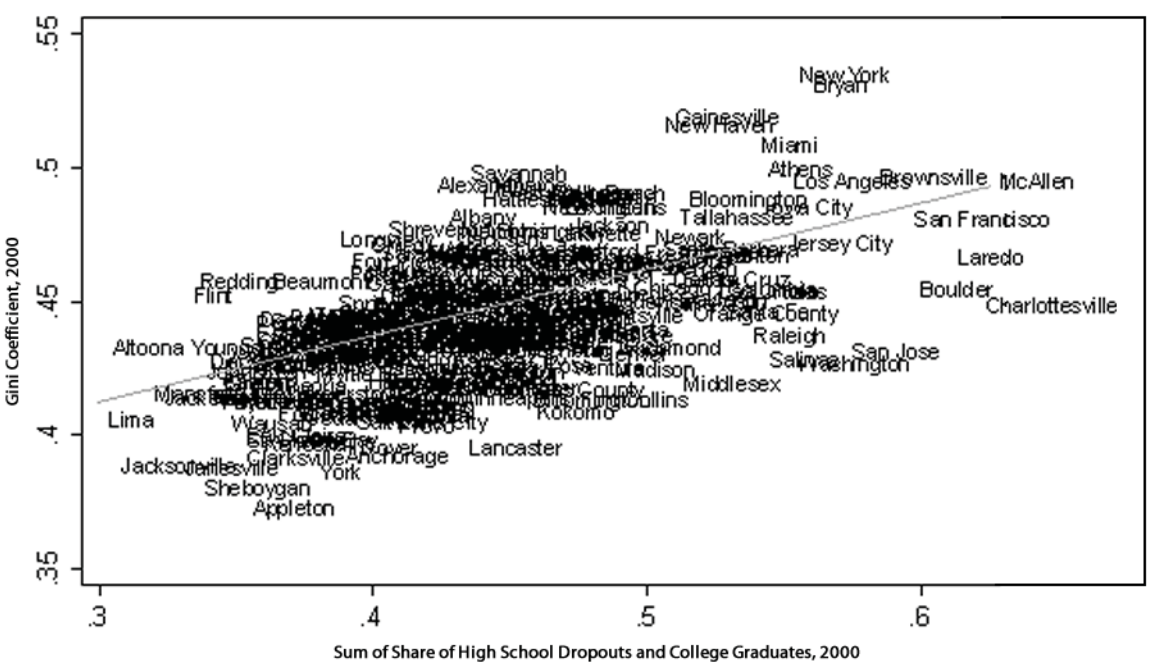
Human Capital Differences and Income Inequality Across Areas

We also examine the role that different skill distributions across places plays in explaining the variation in inequality across places. 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.

We would expect places with a high percentage of college graduates and high percentage of high school dropouts are particularly unequal. When we regress the Gini coefficient on the sum of the share of the population with college degrees and the share of the population who didn't graduate from high school, this aggregate schooling measure can explain 32 percent of the variation in the Gini coefficient, which we show in Figure 3.

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. One approach to this endogeneity is to look at long-standing historical skill patterns Researchers have shown that skill levels are remarkably persistent over time. We find that 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 implies that historical accidents still shape the skill composition of metropolitan areas. Nineteenth century skill measures can also explain skills today. For example, the share

Figure 3: Gini Coefficient and Sum of High School Dropouts and College Graduates, 2000



Source: Gini coefficients are calculated using the 5 percent Integrated Public Use Microdata Series (IPUMS) for 2000, at usa.ipums.org. Share of High School Dropouts and College Graduates is from the 2000 Census.

of the population enrolled in college in 1850 can explain about one-tenth of the variation in the share of the adult population with college degrees today. While this permanence may not be surprising, it suggests that any attempts to shift the skill distribution may take decades to have a discernable impact.

The different distributions of skills, however, do not only reflect these historical forces. Immigration, especially of less skilled workers, also predicts inequality. 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, and the correlation between the percent of population that is Hispanic and the Gini coefficient is .25.[1]

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

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500,000 people. We use only workers with positive earnings, and we use only labor market income, in other words, income from wages. We first calculate the standard Gini coefficient using the earnings from these workers, and there is a 74 percent correlation between this wage 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 wage 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

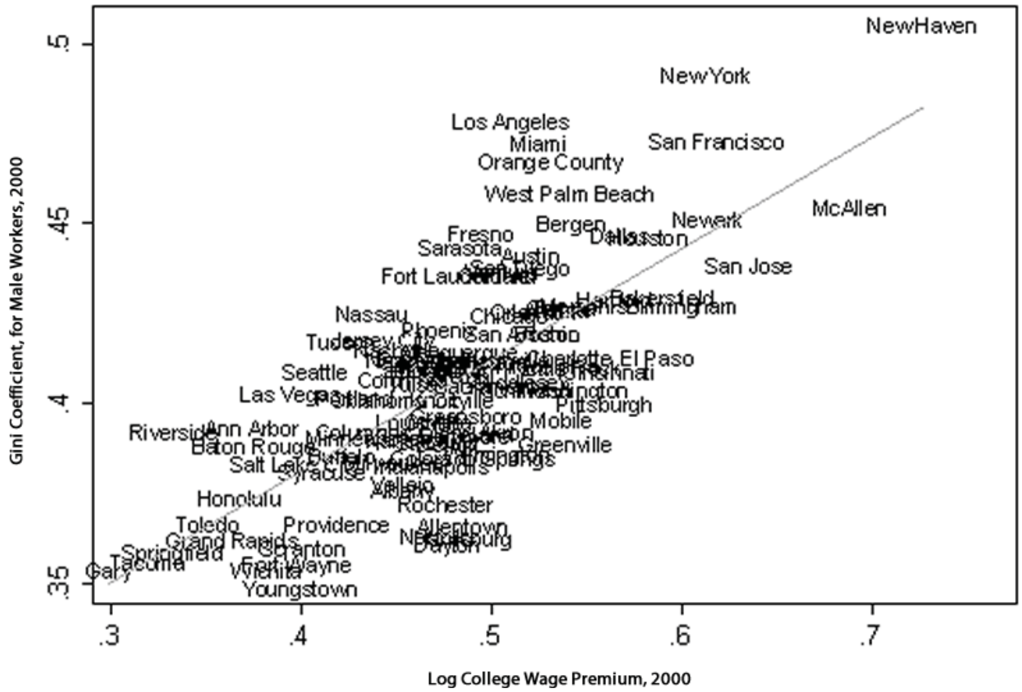
Our Gini coefficient based only on human capital explains about 33 percent of the variation in overall income inequality among working-age males.

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. However, 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.

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. There is a 73 percent correlation between an estimated return to a college degree that we calculate and the Gini coefficient across the 102 areas with more than 500,000 people, which we show in Figure 4. To look at this further, we calculate Gini coefficients for each metropolitan area using wage regressions, allowing the coefficients on skills to differ across metropolitan areas. We again run these regressions only for prime aged males. We then

Figure 4: Gini Coefficient and Returns to College, 2000



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

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 our "human capital only" Gini coefficient 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.

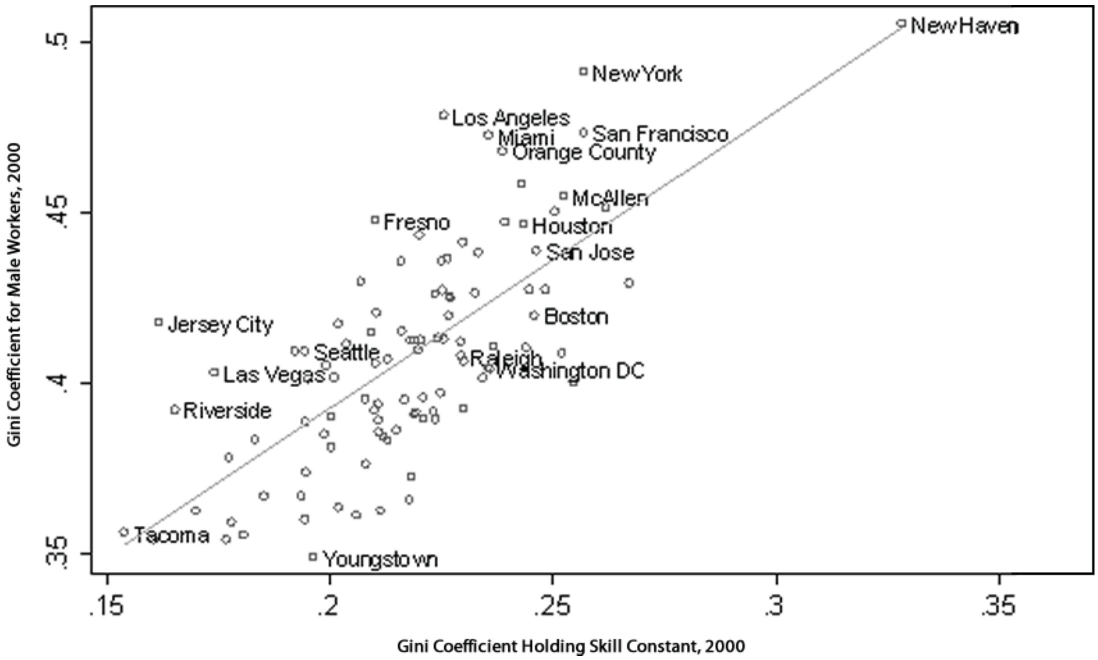
Figure 5 shows the 71 percent correlation between these predicted wage Gini coefficients and actual Gini coefficients in our sample of prime age males across metropolitan areas with more than 500,000 people. The relationship is tighter than it was when we looked at Gini coefficients that assumed a constant 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 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.

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 have brought some understanding to this question, but it remains a pressing topic for future research.

The Consequences of Urban Inequality

In a general sense, local inequality, as opposed to local poverty, is not necessarily a bad thing.

Figure 5: Gini Coefficient and the Gini Coefficient Holding Skills Constant



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

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 or employers, while others suggest that the wealthy develop empathy for the poor through spatial proximity. 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. 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. Our results 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.

Another adverse consequence of inequality is the connection between inequality and crime, which is the subject of a body of research. We duplicate some of these results, and find that the inequality-crime relationship is robust to a number of other controls, and that murder rates increase with inequality. One view for this relationship 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.

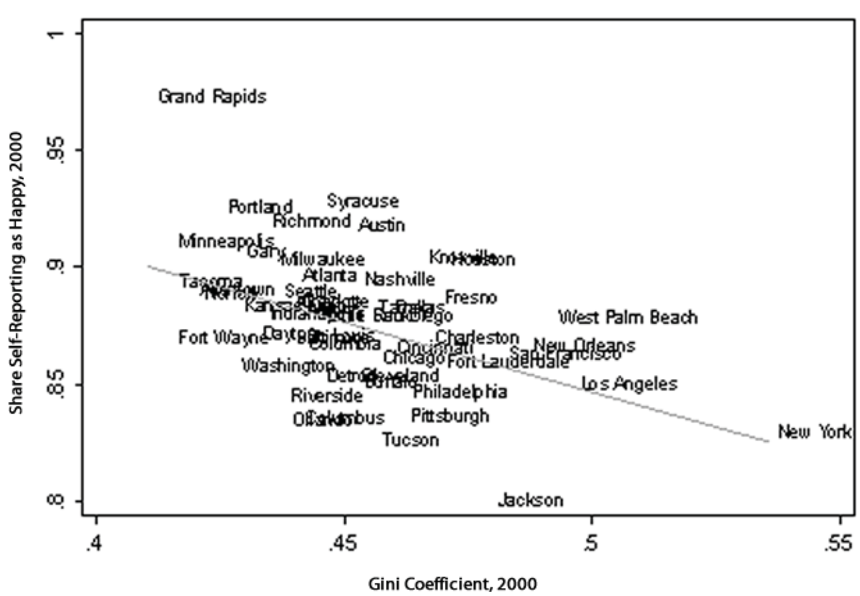
We find also find a -47 percent correlation between the Gini coefficient and the average self-reported happiness in the metropolitan area taken from the General Social Survey, which we show in Figure 6. These happiness data span the last 25 years, and they represent the share of people who say that they 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.

Government Policy

We have already touched on the role that government policy can play in causing inequality, for instance, through immigration policy or education policy that helps determine the levels of skill in different metropolitan areas. However, we must remember that not all reductions in urban inequality are good and not all increases in inequality are bad. If an influx of highly talented entrepreneurs comes to a city, this may both increase employment and increase inequality. Many big city mayors would happily accept the rise in inequality in exchange for the extra economic health. Likewise, an increase in economic vitality in high skilled industries may both increase inequality and increase income levels. Ideally, egalitarian policies would not significantly reduce economic growth.

At the national level, inequality can be reduced with a highly progressive tax rate and redistribution, but at the local level there are a whole host of issues created by the free mobility of people and firms across

Figure 6: Gini Coefficient and Happiness, 2000



space. The tendency of migration to respond to government policies means that local governments face limits (Peterson, 1981) that are different from those faced by the federal government. In particular, many local attempts at redistribution can be completely counterproductive because taxpayers face an exit option. At the local level, attempts to raise taxes to give to the poor can repel the rich and attract the less advantaged. Few localities would actually find it attractive to increase equality by getting rid of the biggest taxpayers and hurting the area's economy. The net result is a reduced tax base and increased segregation. Neither outcome is desirable.

Education offers some hope of creating more equal skill distribution, and more equal skills should eventually lead to a more equal income distribution.

At the local level, just as at the national level, greater welfare gains would seem to be associated with policies that enhance the skills of the less fortunate. Improvements in school districts and reductions in the size of the criminal sector could have two possible benefits, by possibly increasing the skill levels at the bottom end of the income distribution and attracting middle-income people into the area. 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, and 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.

Conclusion

America is a land with much inequality and our cities are places that are often particularly unequal. Urban inequality reflects both the unequal distribution of skills and unequal returns to skill. Inequality is positively related to crime, slow growth, and unhappiness. Yet there are only a limited set of policies that can effectively reduce inequality. At the national level, tax-based redistribution is a possibility, but at the local level, this type of redistribution can be quite counterproductive. When cities try to run local welfare states, the wealthy and businesses tend to flee. Local industrial policy is also likely to have a very limited ability to reduce inequality.

Education offers some hope of creating a more equal skill distribution, and more equal skills should eventually lead to a more equal income distribution. However, it is difficult to make the skill distribution more equal. Improving any school is hard, and it is particularly hard for the federal government to manage the nation's decentralized school system. Still, despite these difficulties, investing in human capital seems like the most promising road towards creating a more equal nation.

FOOTNOTES

1. The connection between inequality and Hispanic immigration emphasizes one of the problems with looking only at local inequality. When immigrants from poor countries come to the U.S., the inequality of American cities may well increase at the same time that global inequality declines. If these immigrants earn more in the U.S. than they did in Mexico, then the world's poor are getting richer through immigration and global inequality is falling. Any attempt to decrease American inequality by reducing the flow of immigrants with only increase inequality world-wide.

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