The Geography of Inequality: Difference and Determinants of Wage and Income Inequality across US Metros

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Abstract:

This paper examines the geographic variation in inequality, and it distinguishes between wage and income inequality. Wage inequality is associated with skills, human capital, technology and metro size - in line with the literature on skill-biased technical change. Income inequality is instead more closely associated with race, poverty, lower levels of unionization and lower taxes. This suggests that income inequality is a product not only of skill-biased technical change, but also of the enduring legacy of race and poverty at the bottom of the socio-economic order, as well as the unraveling of the post-war social compact between capital and labor.

Key words: inequality, income, wage, high-tech, skills.

JEL: J24, O1, O33, R0

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Introduction

Concern regarding inequality in society dates back to the classical economists, especially Marx, who saw it driven by the very logic of capitalism and argued its disruptive tendencies would be as a key factor in its ultimate overthrow. During the golden age of U.S. growth, Kuznets (1955) cautioned about the relationship between economic growth and income inequality, calling for increased scholarship to better understand this phenomenon.

Today, inequality has once again surged to the fore of popular debate. A large number of economic studies (Murphy, Riddell and Romer, 1998; Card and DiNardo 2002; Autor, Katz and Kearney 2008) have documented the sharp rise in inequality over the past several decades. As Nobel Prize winning economist, Joseph Stiglitz, frames it: "The upper 1 percent of Americans are now taking in nearly a quarter of the nation's income every year. In terms of wealth rather than income, the top 1 percent control 40 percent," adding that: "Twenty-five years ago, the corresponding figures were 12 percent and 33 percent." He then cautioned: "One response might be to celebrate the ingenuity and drive that brought good fortune to these people, and to contend that a rising tide lifts all boats. That response would be misguided. While the top 1 percent have seen their incomes rise 18 percent over the past decade, those in the middle have actually seen their incomes fall. For men with only high-school degrees, the decline has been precipitous—12 percent in the last quarter-century alone. All the growth in recent decades—and more—has gone to those at the top" (Stiglitz, 2011).

While much of the conversation has focused on the avarice and privileges of the top one percent, most economists argue that rising inequality has been driven by broader structural changes in the economy. As the middle of good-paying blue collar

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jobs has disappeared as a consequence of deindustrialization, globalization and automation, the job market has literally been biurificated. On one side are higher-paying, professional, knowledge and creative jobs that require considerable education and skill. And on the other are an even larger and faster growing number of more routine jobs in fields like personal care, retail sales and food service and preparation that pay much lower wages. This in turn underpins a broader set of social, cultural, geographic, income, and other inequalities.

A leading explanation revolves around the construct of "skill-biased technical change" (Autor, Katz & Kearney, 2006; Autor, Kazt & Krueger, 1998; Autor, Levy and Murnane, 2003). The combination of globalization and the shift of manufacturing to lower wage counties like China, dubbed "the world's factory," new technologies of robotics and automation, and increases in productivity and efficiency have eliminated millions of formerly low-skill but high-paying jobs. Goldin and Katz (2008) document the relationship between technological change and increasing returns to education and skills as shaping growing inequality. Acemoglu (1998) provides a theoretical rationale for this connection between skill-based technical change and rising inequality.

Numerous studies have noted the intersection of race and poverty in the United States. Wilson (1990) identified the intersection of poverty and race, brought on by economic restructuring and shaping the circumstance of the "truly disadvantaged." Gordon and Dew-Becker (2008) and Deininger and Squire (1996) document the connection between of economic growth and poverty reduction.

A large body of research identifies the connection between rising inequality and the unraveling of the post-war social compact between capital and labor. Unionization helped to raise the wages of factory workers and create a larger middle

class according to this view. While more progressive taxation helped redistribute income, mitigate inequality and underpin middle class society. In the 1980s and 1990s, Bluestone and Harrison (1982, 1986, 1988, 1990) pointed to the declining rate of unionization as a key factor in shrinking wages and rising inequality. Others have argued that lower tax rates, especially on higher income individuals, have also worked to heighten inequality. Stiglitz (1969) showed how taxes redistribute incomes and increase the rate at which wealth is equalized. Korpi and Palme (1998) have argued that outcomes of market-based distributions are more unequal that those of earnings- and tax-related social insurance programs. Taken together, de-unionization and lower tax rates reflect the unraveling of the post-war social compact, according to this line of research.

Our research focuses on the geography of inequality. A number of recent studies point to the role and effects of geography on inequality. For one, large cities and metros have been found to have distinct advantages when it comes to attracting high-skill people, high-tech jobs, and other economic assets in more global knowledge based economies As a result, there has been a divergence in the location of high human capital workers and households and an attendant divergence in the economic fortunes of cities and regions (Berry and Glaeser, 2005; Florida, 2002a; Florida, 2002b; Florida et al, 2008). Studies by Bacold, Blum and Strange (2009) and Florida et al. (2011) find that the distribution of skills varies across different types of cities, with higher wage social analytical skills being concentrated in large metros, and lower-wage physical skills concentrated in smaller ones. When Glaeser, Resserger and Tobio (2009) examined patterns of local level inequality, they used a modified Gini coefficient, and found that a connection between urban inequality and the clustering of ore and less skilled people in particular areas. "City-level skill

inequality," they note, "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" (p. 617).

Baum-Snow and Pavan (2011) found a close connection between city size and inequality, demonstrating city-size alone accounted for roughly 25 to 35 percent of the total increase in economic inequality over the past three decades, after the role of skills, human capital, industry composition and other factors were taken into account. Moreover, city size plays an ever greater role in explaining the plight of the lowest wage worker, accounting for 50 percent more of the increase in inequality for the lower half of the wage distribution than for the upper half.

Our research seeks to shed light on the geography of inequality. While most studies of inequality look at national patterns of inequality over time or across nations, our research focuses on difference in inequality across more than 350 U.S. metro areas. The factors that bear on inequality – from human capital and skill, to race, poverty, unionization and tax rates - vary considerably across geography, enabling us to parse the relative effects of each. A novel aspect of our research involves examining two distinct types of inequality – wage inequality and income inequality – and identifying the factors that bear on each.

The main findings of our analysis suggest that wage inequality and income inequality are very different things. We find a relatively small association between the two. Wage inequality, according to our analysis and models, wage inequality, explains only 16 percent of income inequality across U.S, metros. Furthermore, we find that wage inequality and income inequality appear to results from different sets of factors. Wage inequality, on the one hand, is associated with the kinds of things that the literatures on skill-biased change and regional human capital divergence point to –

factors like, human capital levels, occupational structure, skills and metro size. Income inequality, on the other hand, is associated with factors more closely identified with the literatures on race and poverty. We find income inequality is more strongly associated with poverty, race, de-unionization and low income taxation rates-factors that play at best a modest role in wage inequality.

Variables Data and Methods

We now describe the methods, variables and data used in our analysis. *Income Inequality* is measured as a Gini coefficient. This variable captures the distribution of incomes from the bottom to the top. Given that the Census does not publish individual incomes above $100,000; we cannot calculate the Gini coefficient ourselves. Instead, we use the three-year estimate of the coefficient provided by the 2010 American Community Survey.

Wage Inequality – This variable is calculated as a Theil index, which is an entropy measure which will capture differences in wage between occupational groups of knowledge workers, standardized service workers, manufacturing workers, and fishing and farming workers. Given restricted data availability about top incomes, we cannot calculate a Gini coefficient for wage inequality, but rather have to use inequality in between groups formulated as a Theil index using 2010 data from the Bureau of Labor Statistics.

Average Income – This is the sum of the amounts reported separately for wage or salary income including net self-employment income. It is measured on a per capita basis and is from the 2010 US Census.

High-Tech – This is a measure of regional concentration of high-technology industry. The measure is based on the Tech-Pole Index (Devol et al, 2001), which captures the

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percentage of the region's own total economic output that comes from high-tech industries, in relation to the nationwide percentage high-tech industrial output as a percentage of total U.S. high-tech industrial output. This data is from the Census County Business Patterns for 2010.

Human Capital – We employ a measure for the share of the labor force with a bachelor's degree or more, from the 2010 Census American Community Survey.

Creative Class – This variable measures the share of creative occupations in which individuals, "engage in complex problem-solving that involves a great deal of independent judgment and requires high levels of education or human capital" (Florida, 2002a, p. 8). More specifically, it includes computer and mathematics occupations; architecture and engineering; life, physical, and social science; education, training, and library positions; arts and design work; and entertainment, sports, and media occupations. It also includes professional and knowledge-work occupations such as management occupations, business and financial operations, legal positions, health-care practitioners, technical occupations, and high-end sales and sales management. The data is for the year 2010 from the Bureau of Labor Statistics.

Skills – This variable covers the two skill types most associated with high-skill non-routine work: analytical skills and social skills. Analytical skills refer to general cognitive functioning, numerical capabilities, and the ability to develop and use rules to solve problems. Social skills include those such as deductive reasoning and judgment decisions to find the answers to complex problem solving situations (see: Florida et al, 2011). The data is derived from the O*NET database from the Bureau of Labor Statistics for the year 2007.

Race – This variable measures the African-American share of the population and is from the 2010 American Community Survey.

Metro Size– This is a measure of metro population size for the year 2010, from the Census American Community Survey.

Change in Housing Values – This variable measure of the change in median housing value between the years 2000 and 2008. The data is from the US Census Bureau.

Taxation (Tax Revenue as Percentage of Personal Income) – This is the tax revenue as a percentage of personal income by state. The data is for the year 2007 from US Census.

Unionization: We employ a measure for the share of the employed workers that are union members. The data is from http://unionstats.com and is for the year 2010.

Poverty – This variable measures the share of the population that is below the poverty line. It is based on data is from the American Community Survey for the years 2007-2009.

High-Income Share – It measures the share of the population that belongs to the highest income group ($10,000 and above) according to the American Community Survey for the years 2007-2009.

Table 1 provides descriptive statistics for these variables.

(Table 1 about here)

Mapping Wage and Income Inequality

We not turn to the findings from our analysis. To orient the discussion that follows, Figure 1 provides maps of the two types of inequality that are the subject of our analysis: wage inequality and income inequality.

(Figure 1 about here)

Figure 1 maps the geography of wage inequality across U.S. metros. The measure is based on the Theil Index, which is an entropy measure which will capture differences in wage between occupational groups of knowledge workers, standardized service workers, manufacturing workers, and fishing and farming workers. It is based 2010 data from the Bureau of Labor Statistics.

As the map shows, the variation in wage inequality across metros is considerable, ranging from a low of .22 to a high more than double that of .48-.50. The metros with the highest wage inequality scores are almost all major high-tech knowledge economy regions such as Huntsville, Alabama (a center for semiconductor and high-tech industry); San Jose (the fabled Silicon Valley); College Station-Bryan, Texas (home to Texas A&M); ; Boulder, Colorado (a leading center for tech startups); Durham, North Carolina in the famed Research Triangle is fifth, and Austin (another leading high-tech center), as well as large, diverse metros such as New York, Los Angeles, greater Washington DC and San Francisco - all of which number among the top twenty metros with the most unequal wages.

(Figure 2 about here)

Figure 2 maps the geography of income inequality, measured as a Gini coefficient based on data from the 2010 American Community Survey. The two maps are strikingly different. Knowledge-based high-tech metros do not score highly on income inequality. The most unequal metros are a mix of large metros, like Bridgeport-Stamford, Connecticut; greater New York and greater Miami But the

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majority of the most unequal metros in terms of income are smaller metros, including many resort and college towns.

(Figure 3 about here)

Figure 3 plots metros on the two measures of inequality. It arrays into four basic quadrants. Metros in the upper right-hand corner face the double whammy of high income and high wage inequality. Metros in the lower right have relatively high levels of wage inequality alongside relatively lower levels of income inequality. Metros in the upper left have high levels of income inequality alongside relatively lower levels of wage inequality. Lastly, metros in the lower left have relatively low levels of both.

It shows that while wage and income inequality overlap to a certain degree, there is not a necessary connection between these two types of inequality. There are metros with high levels of both wage and income inequality, as well as metros with low levels of both. But there are also metros with higher levels of income inequality than what their wage inequality level would predict, as well as metros with lower levels of income equality than what their wage inequality would predict.

Correlation Analysis

The next step in our analysis is a basic correlation analysis to better gauge the how are main variables are associated with the two types of inequality, wage and income inequality. Table 2 summarizes its key findings. Here the results point to some interesting patterns and differences.

(Table 2 about here)

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First off, the correlation between the two measures of inequality – wage and income inequality is .408, which is moderate but not overwhelming. While the two are associated, one does not fully explain the other.

Wage inequality conforms to most of the factors identified in the literature on skill-biased technology change and regional skills and economic divergence. Wage inequality reasonably associated with human capital (.606), knowledge-based and creative occupations (.666), high-tech industry (.625), analytical and social skills (.530), high-income share (.600), average income levels (.425) and metro size (.476). It is not significantly associated with poverty and only modestly associated with race (.201) and. As for factors that bear on the post-war social compact, it is not associated with taxation and only weakly related to unionization (-.149).

Income inequality on the other hand is more closely related to race, poverty and indicators of the unraveling of the social compact (de-unionization and lower rates of taxation). It is most closely associated with poverty (.475) and slightly less so to race (.296). It is negatively associated with unionization (-.336), in other words inequality is higher in metros with lower levels of unionization; and it is also negatively associated with taxation (-.233), inequality is higher in metros with lower rates of taxation. It is modestly associated with some of the factors identified in the literatures on skill-biased technical change and regional skill divergence, such as: human capital (.262), the high-income share of the population (.281), metro size (.242), workforce skill (.210), high-tech industry (.201), and knowledge and creative occupations (.188). It is not significantly associated with average income or changes in housing values.

To a certain degree, this result is not a huge surprise, as income inequality measured by the Gini coefficient captures the income distribution from the bottom to

the top. In other words, the share below the poverty line should be reflected by the lower part of the Lorenz curve and the share in the top income group the higher part of the Lorenz curve (which is used to estimate the Gini). However, if incomes are high in general in a region, only a very restricted, and small, part would be equal to the lower part of the Lorenz curve (and the opposite for high income share), and not necessarily have a major impact on the overall distribution.

(Figure 4 about here)

Figure 4 is s a scatter-graph that compares income inequality to poverty. The scatter-graph reveals a fairly linear, but not identical, relationship between income inequality and poverty shares. A number of regions have low shares of poverty (e.g. Bridgeport, Naples, New York, Miami, Boston and San Francisco) but still levels of income inequality that are relatively high. There are also regions with low levels of income inequality, but with relatively high shares of poverty (e.g. Hanford, CA, Clarksville, TN-KY, and Hinesville, GA). Thus, as this figure shows, the relationship between the poverty and the Gini coefficient is not simply one of default.

(Figure 5 about here)

Figure 5 is s scatter-graph of income inequality and the high-income share scatter plot of the population. The relationship between the two variables is less linear than between income inequality and poverty. There are places with high levels of income inequality and small shares of high-income individuals. Conversely, there are also metros with relatively low levels of income inequality and relatively large shares of high-income people. The correlation between income inequality and the share of

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high-income people is insignificant (-.070), while the correlation between income inequality and poverty is positive and significant (.475). This suggests that income inequality is being more related to the bottom of the socio-economic order than the top of it.

Multiple Regression Analysis

To further understand the interplay and determinants of wage and income inequality, we turn to the results of our multiple regression analysis. Our model is estimated by a basic OLS regression with income inequality as the dependent variable and a series of independent variables. The model is designed to test the explanatory power of wage inequality and other factors such as skills and high-tech industry shares. At the same time, we include socio-economic control variables which also can be assumed to be related to income inequality, such as average income, race, changes in housing values, income taxation rates, poverty shares, high-income shares, unionization, and metro size to determine income inequality. All variables are in logged form, and the coefficients can be interpreted as elasticities. Table 3 and 4 summarizes the key results from the regressions. First, we ran models with the three skills variables (human capital, creative class and skills) one at a time to limit multicollinarity issues (Table 3).

(Table 3 about here)

Equation 1 models the basic relationship between wage inequality and income inequality alone. Wage inequality, while significant, explains just 16 percent of the variation in income inequality across regions.

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Equation 2 adds two additional variables - average income and high-tech. The R2 Adj. increases just slightly to .180. High-tech is weakly significant. And surprisingly, there is a negative and significant relation between average income and income inequality. This suggests that metros with higher levels of average incomes have lower levels of income inequality. Average incomes can increase in several ways; the poor do better; the rich do better, or everybody does better. This suggests that the gap between the bottom and the top gets closer, as the average income in regions increases.

Equation 3 adds human capital, measured as the percentage of adults with at least a college degree or above. The R2 Adj. increases slightly to .203. Human capital is positive and significant, meaning that income inequality is greater in metros with higher shares of highly educated people. Wage inequality and average income remain significant, while high tech concentration loses its significance

Equation 4 substitutes the variable for human capital with that of the creative class. The R2 Adj. is slightly lower .188. The occupation variable is insignificant, indicating that income inequality is not related to higher shares of creative class workers. Equation 5 substitutes the skill variable, leading to similar results.

Overall, our results suggest that income inequality is most closely associated with average income levels, human capital and to some extent high-tech industry. Creative class occupations and underlying workforce skills are insignificant once wage inequality, average income and high-tech are controlled for. Based on this, we will now exclude creative class and skills from our regressions, in order to add other socio-economic variables to the model, such as race, poverty, unionization, high-income share, change in housing values, and taxation. We also add a control variable

for metro size, to examine if bigger regions are more unequal. Table 4 summarizes these results.

(Table 4 about here)

Equation 6 introduces race, change in housing values, taxation and metro size. This doubles the R2 Adj. values to .323, with positive and significant values for race and metro size, while taxation is negative and significant. This indicates that metros with higher shares of African-Americans and lower rates of taxation have higher levels of income inequality. Since we expect a strong collinearity between these variables, we also generated variance inflation factor values, which indicate that there is a relatively strong association between high-tech and metro size. We re-ran equation 6 and included high-tech and metro size one at a time. Run individually, each variable is also turned out to be insignificant. We also created an interaction variable for high-tech and metro size, and it was also insignificant in this model. We thus exclude both variables in the following regressions.

In Equation 7, we add poverty and the share of high-income people. Studies by Gordon and Dew-Becker (2008), Deininger and Squire (1996) have demonstrated the consequences of poverty on levels of inequality. We note that poverty partly may be a proxy for the lower part of the Lorenz curve, while high income share is a reflection of the top of the Lorenz curve, which determines the slope of the Gini coefficient. Since this will impact the explanatory value of our model (and increase the R2 values), we add them to the model in combination, as well as one by one. Both variables are significant, as expected. But interesting enough, the poverty variable is much stronger than the high-income variable. In other words, the share of the population below the poverty line explains more of income inequality than the share

of people with high incomes. Wage inequality, race, and taxation rates all remain significant.

In Equation 8, we only include poverty and in Equation 9, we only include high-income share, in order to be parse the relative effects of each. The regression with poverty generates an R2 adjusted of .580, substantially higher than that R2 of .325 for the regression with the high-income share variable. It is important to point out that our variable for high-income share is limited by the fact that the cut-off is $100,000 (based on the definition from the Census), and as a result, we cannot determine the exact slope of the Lorenz curve. That said, our findings still suggest income inequality is more strongly related to poverty, in other words with the bottom end of the income distribution, than to the top end of it.

In the last Equation (10), we include the unionized share of the labor force. Including it reduces our sample by one-third, due to lack of data, and this may have an effect on the estimations overall. Unionization is negative and significant. In other words, unionization has a dampening effect on income inequality across metros regions. It was found that the higher the share of union membership, the lower the income inequality. Average income remains significant in this model, but human capital does not. When we check for multicollinearity, we find relatively high VIF values between average income and human capital. To better understand this, we ran income and human capital separately. Now each variable is significant. We then created a single interaction term from both the income and human capital variables, and it is also significant. Thus we are led to conclude human capital remains associated with income inequality as well, and that the insignificant sign is a result of multicollinearity in the model. We also re-ran Equation 10 with the smaller sample, but without the unionization variable. Wage inequality, human capital, and race

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remained insignificant. Therefore, we conclude that the insignificance of these values in Equation 10 is due to the reduced sample size rather than the inclusion of the unionization variable

Discussion and Conclusions

Our research has examined the geography inequality across the United States. It distinguished between two distinct types of inequality: wage and income inequality. We mapped and charted the variation in each across U.S. metros and presented the results of the correlation and regression analysis examining a range of factors that the literatures on skill-biased technical changes and regional human capital and economic divergence, on the one hand and on race, class, and poverty, on the other, suggest are associated with inequality.

Perhaps the most striking finding of our analysis is that when looked at geographically – that is across U.S. metros –these two types of inequality turn out to be quite different from one another. The two are only modestly correlated with one another; and wage inequality explains 16 percent of income inequality.

The two are also associated with very different clusters of variables, according to our analysis. Wage inequality is most closely associated by the factors identified in the literatures on skill-biased technical change and regional skills and economic divergence, Wage inequality is higher in larger, more skilled regions, with higher levels of human capital, greater shares of creative class jobs, and greater concentrations of high-tech industry.

But, the story is rather different when it comes to income inequality based on the Gini coefficient. Income inequality is less closely associated with these factors and more closely associated poverty and race (Wilson 1990) as well as de-

unionization (Bluestone and Harrison, 1988), and low tax rates. The results for race and poverty suggest that income inequality is strongly related to the sagging bottom of the socio-economic order. This is reinforced by the finding that inequality is negatively associated with average incomes, which suggest that more affluent metros are not necessarily more unequal. We also find that while income inequality is positively associated with the high-income share of the population, this associating is not strong as with poverty. We are thus led to conclude that income inequality across U.S. metros is more a consequence of the sagging at the bottom of socio-economic order.

Geographic factors also appear to play different roles in the two types of inequality. Metro size is closely related wage inequality, but is not associated with income inequality when we control for other socio-economic variables. The geographic sorting of the population across human capital and skill groups which plays such a large role in wage inequality does appear to play much of a role, if any, in the incidence of income inequality across metros.

For all these reasons, we suggest that future research focus on the differences and distinctions in these two kinds of inequality. While much of the current literature focuses on the effects of skill-biased technical change and in the structural economic transformation, our findings remind us of the ongoing role of race and poverty in income inequality. Our best assessment based on the findings of this research is that overall inequality is that skill-biased technical change is a necessary but insufficient condition for explaining overall inequality across U.S. metros. The enduring legacy of race and poverty and the unraveling of the post-war social compact reflected in, de-unionization and low tax rates play significant roles as well. Thus, policy measures designed to address inequality should deal with all of these factors. Most of all we

hope our research and findings spur additional research on the geographic causes and

consequences of inequality

References:

Acemoglu, D. (1998). Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality. *The Quarterly Journal of Economics*, *113*(4), 1055 -1089. doi:10.1162/003355398555838

Acemoglu, D., & Robinson, J. (2011). *Why Nations Fail: The Origins of Power, Prosperity, and Poverty*. Crown.

Adams, Jr., R. (2003). Economic Growth, Inequality, and Poverty: Findings from a New Data Set. *SSRN eLibrary*. Retrieved from: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1357182

Atkinson, A., Piketty, T., & Saez, E. (2011). Top Incomes in the Long Run of History. *Journal of Economic Literature*, *41*(9), 3-71. doi: Urban inequality: evidence from four cities

Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The Polarization of the U.S. Labor Market. *National Bureau of Economic Research Working Paper Series*, *No. 11986*. Retrieved from http://www.nber.org/papers/w11986

Autor, D. H., Katz, L. F., & Krueger, A. B. (1998). Computing Inequality: Have Computers Changed the Labor Market?. *Quarterly Journal of Economics*, *113*(4), 1169-1213. doi:10.1162/003355398555874

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics*, *118*(4), 1279-1333. doi:10.1162/003355303322552801

Ballas, D. (2004). Simulating Trends in Poverty and Income Inequality on the Basis of 1991 and 2001 Census Data: A Tale of Two Cities. *Area*, *36*(2), 146-163. doi:10.1111/j.0004-0894.2004.00211.x

Bartels, L. M. (2010). *Unequal Democracy: The Political Economy of the New Gilded Age*. Princeton University Press.

Baum-Snow, N., & Pavan, R. (2011). *Inequality and City Size* (pp. 1-33). The National Bureau of Economic Research. Retrieved from http://www.econ.brown.edu/fac/Nathaniel_Baum-Snow/ineq_citysize.pdf

Berry, C. R., & Glaeser, E. L. (2005). The Divergence of Human Capital Levels Across Cities. *Papers in Regional Science*, *84*(3), 407-444. doi:10.1111/j.1435-5957.2005.00047.x

Betz, D. M. (1974). A Comparative Study of Income Inequality in Cities. *The Pacific Sociological Review*, *17*(4), 435-456.

Bishop, B. (2008). *The Big Sort: Why the Clustering of Like-Minded America Is Tearing Us Apart* (None.). Houghton Mifflin Harcourt.

Bluestone, B., & Harrison, B. (1982). *The Deindustrialization of America: Plant Closing, Community Abandonment, and the Dismantling of Basic Industry*, New York: Basic Books.

Bluestone, B., & Harrison, B. (1986). *The Great American Job Machine: The Proliferation of Low Wage Employment In the US Economy*, Study prepared for the Joint Economic Committee, available at: http://www.eric.ed.gov/ERICWebPortal/search/detailmini.jsp?_nfpb=true&_&ERICExtSearch_SearchValue_0=ED281027&ERICExtSearch_SearchType_0=no&accno=ED281027

Bluestone, B., & Harrison, B. (1988). The Growth of Low-Wage Employment: 1963-86, *The American Economic Review*, 78(2), 124-128.

Borjas, G. J. (1995). The Internationalization of the U.S. Labor Market and the Wage Structure. *Economic Policy Review*, 1(1): 3-9. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1029649

Borjas, G. J., & Ramey, V. A. (1995). Foreign Competition, Market Power, and Wage Inequality. *The Quarterly Journal of Economics*, *110*(4), 1075 -1110. doi:10.2307/2946649

Braun, D. (1988). Multiple Measurements of U.S. Income Inequality. *The Review of Economics and Statistics*, *70*(3), 398-405. doi:10.2307/1926777

Burgers, J., & Musterd, S. (2002). Understanding Urban Inequality: A Model Based on Existing Theories and an Empirical Illustration. *International Journal of Urban and Regional Research*, *26*(2), 403-413. doi:10.1111/1468-2427.00387

Card, D., & DiNardo, J. E. (2002). Skill Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles. *National Bureau of Economic Research Working Paper Series*, *No. 8769*. Retrieved from: http://www.nber.org/papers/w8769

Colenutt, B. (1970). Poverty and Inequality in American Cities. *Antipode*, *2*(2), 55-60. doi:10.1111/j.1467-8330.1970.tb00481.x

Collins, R. W., & Morris, R. A. (1988). Racial Inequality in American Cities: An Interdisciplinary Critique. *National Black Law Journal*, *11*, 177.

Deininger, K., & Squire, L. (1996). A New Data Set Measuring Income Inequality. *The World Bank Economic Review*, *10*(3), 565 -591. doi:10.1093/wber/10.3.565

DeVol, R., Wong, P., Catapano,J., & Robitshek,G. (2001) *America's High-Tech Economy; Growth, Development, and Risks for Metropolitan Areas*, Milken Institute.

Donegan, M., & Lowe, N. (2008). Inequality in the Creative City: Is There Still a Place for "Old-Fashioned" Institutions? *Economic Development Quarterly*, *22*(1), 46 - 62. doi:10.1177/0891242407310722

Fan, C. C., & Casetti, E. (1994). The spatial and temporal dynamics of US regional income inequality, 1950–1989. *The Annals of Regional Science*, *28*(2), 177-196. doi:10.1007/BF01581768

Florida, R. (2002a). *The Rise Of The Creative Class: And How It's Transforming Work, Leisure, Community And Everyday Life* (1st ed.). Basic Books.

Florida, R. (2002b). The Economic Geography of Talent. *Annals of the Association of American Geographers*, *92*(4), 743-755. doi:10.1111/1467-8306.00314

Florida, R., Mellander, C., & Stolarick, K. (2008). Inside the black box of regional development—human capital, the creative class and tolerance. *Journal of Economic Geography*, *8*(5), 615 -649. doi:10.1093/jeg/lbn023

Florida, R., Mellander, C., Stolarick, K., & Ross, A. (2011). Cities, skills and wages. *Journal of Economic Geography*. doi:10.1093/jeg/lbr017

Gabbidon, S. L., & Greene, H. T. (2005). *Race, crime, and justice: a reader*. Routledge.

Gavin, S. (2007). Global cities of the South: Emerging perspectives on growth and inequality. *Cities*, *24*(1), 1-15. doi:10.1016/j.cities.2006.10.002

Glaeser, E. L., Resseger, M., & Tobio, K. (2009). Inequality in Cities. *Journal of Regional Science*, *49*(4), 617-646. doi:10.1111/j.1467-9787.2009.00627.x

Goldin, C. D., & Katz, L. F. (2008). *The race between education and technology*. Harvard University Press.

Goldsmith, W. W., Blakely, E. J., & Clinton, B. (2010). *Separate Societies: Poverty and Inequality in U.S. Cities*. Temple University Press.

Gordon, R. J., & Dew-Becker, I. (2008). Controversies about the Rise of American Inequality: A Survey. *National Bureau of Economic Research Working Paper Series*, *No. 13982*. Retrieved from http://www.nber.org/papers/w13982

Gould, E. D. (2007). Cities, Workers, and Wages: A Structural Analysis of the Urban Wage Premium. *Review of Economic Studies*, *74*(2), 477-506. doi:10.1111/j.1467-937X.2007.00428.x

Gould, Eric D., & Paserman, M. D. (2003). Waiting for Mr. Right: Rising Inequality and Declining Marriage Rates. *Journal of Urban Economics*, *53*(2), 257-281. doi:10.1016/S0094-1190(02)00518-1

Hunter, B. H. (2003). Trends in Neighbourhood Inequality of Australian, Canadian, and United States of America CitiesSsince the 1970s. *Australian Economic History Review*, *43*(1), 22-44. doi:10.1111/0004-8992.00039

Hunter, B., & Gregory, R. G. (1996). An Exploration of The Relationship Between Changing Inequality Of Individual, Household And Regional Inequality In Australian Cities. *Urban Policy and Research*, *14*(3), 171-182. doi:10.1080/08111149608551594

Korpi, W., & Palme, J. (1998). The Paradox of Redistribution and Strategies of Equality: Welfare State Institutions, Inequality, and Poverty in the Western Countries, American Sociological Review, 63(5), 661-687.

Kuznets, S. (1955). Economic Growth and Income Inequality. *The American Economic Review*, *45*(1), 1-28.

Lerman, R. I., & Yitzhaki, S. (1985). Income Inequality Effects by Income Source: A New Approach and Applications to the United States. *The Review of Economics and Statistics*, *67*(1), 151-156. doi:10.2307/1928447

Martin, R. (1997). Can High-Inequality Developing Countries Escape Absolute Poverty? *Economics Letters*, *56*(1), 51-57. doi:10.1016/S0165-1765(97)00117-1

McCall, L. (2000). Explaining Levels of Within-Group Wage Inequality in U.S. Labor Markets. *Demography*, *37*(4), 415-430. doi:10.1353/dem.2000.0008

McCall, L. (2001). Sources of Racial Wage Inequality in Metropolitan Labor Markets: Racial, Ethnic, and Gender Differences. *American Sociological Review*, *66*(4), 520-541. doi:10.2307/3088921

Mincer, J. (1996). Economic Development, Growth of Human capital, and the Dynamics of the Wage Structure. *Journal of Economic Growth*, *1*(1), 29-48. doi:10.1007/BF00163341

Moretti, E. (2008). Real Wage Inequality. *National Bureau of Economic Research Working Paper Series*, *No. 14370*. Retrieved from: http://www.nber.org/papers/w14370

Murphy, K., Riddell, C., and Romer, P. (1998). Wages, Skill, and Technology in the United States and Canada, in *General Purpose Technologies and Economic Growth*,

Elhanan Helpman, Ed. Cambridge, MA and London: MIT Press.

Nord, S. (1980). An Empirical Analysis of Income Inequality and City Size. *Southern Economic Journal*, *46*(3), 863-872. doi:10.2307/1057154

Obama, Barack (2011). Remarks by the President on the Economy in Osawatomie, Kansas, December 6, 2011, Available at: http://www.whitehouse.gov/the-press-office/2011/12/06/remarks-president-economy-osawatomie-kansas

O'Connor, A., Tilly, C., & Bobo, L. (2001). *Urban Inequality: Evidence From Four Cities*. Russell Sage Foundation.

Semyonov, M., Haberfeld, Y., Cohen, Y., & Lewin-Epstein, N. (2000). Racial Composition and Occupational Segregation and Inequality across American Cities. *Social Science Research*, *29*(2), 175-187. doi:10.1006/ssre.1999.0662

Shihadeh, E. S., & Steffensmeier, D. J. (1994). Economic Inequality, Family Disruption, and Urban Black Violence: Cities as Units of Stratification and Social Control. *Social Forces*, *73*(2), 729 -751. doi:10.1093/sf/73.2.729

Smith, S. S. (2000). Mobilizing Social Resources: Race, Ethnic, and Gender Differences in Social Capital and Persisting Wage Inequalities. *The Sociological Quarterly*, *41*(4), 509-537. doi:10.1111/j.1533-8525.2000.tb00071.x

Steelman, A., & Weinberg, J. A. (2005). *What's Driving Wage Inequality?* (pp. 1-17). Federal Reserve Bank of Richmond. Retrieved from: http://www.richmondfed.org/publications/research/economic_quarterly/2005/summer/pdf/steelmanweinberg.pdf

Stephens, C. (1996). Healthy Cities or Unhealthy Islands? The Health and Social Implications of Urban Inequality. *Environment and Urbanization*, *8*(2), 9 -30. doi:10.1177/095624789600800211

Stiglitz, J. E. (1969). Distribution of Income and Wealth Among Individuals, Econometrica, 37(3), 382-397.

Stiglitz, J. (May 2011) "Of the 1%, by the 1%, for the 1%," *Vanity Fair*. Retrieved from: http://www.vanityfair.com/society/features/2011/05/top-one-percent-201105?currentPage=all&wpisrc=nl_wonk

Tanzi, V., & Chu, K.Y. (1998). *Income Distribution and High-Quality Growth*. MIT Press.

Timberlake, J. M., & Iceland, J. (2007). Change in Racial and Ethnic Residential Inequality in American Cities, 1970–2000. *City & Community*, *6*(4), 335-365. doi:10.1111/j.1540-6040.2007.00231.x

Wheeler, C. (2005a). *Evidence on Wage Inequality, Worker Education and Technology* (pp. 375-395). Federal Reserve Bank of St. Louis Review. Retrieved from http://65.89.18.138/publications/review/05/05/Wheeler.pdf

Wheeler, C. H. (2004). Wage Inequality and Urban Density. *Journal of Economic Geography*, *4*(4), 421 -437. doi:10.1093/jnlecg/lbh033

Wheeler, C. H. (2005b). Cities, Skills, and Inequality. *Growth and Change*, *36*(3), 329-353. doi:10.1111/j.1468-2257.2005.00280.x

White, M. J. (1981). Optimal Inequality in Systems of Cities or Regions. *Journal of Regional Science*, *21*(3), 375-387. doi:10.1111/j.1467-9787.1981.tb00707.x

Wilson, W. J. (1990). *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy* (1st ed.). University Of Chicago Press.

FIGURES AND TABLES

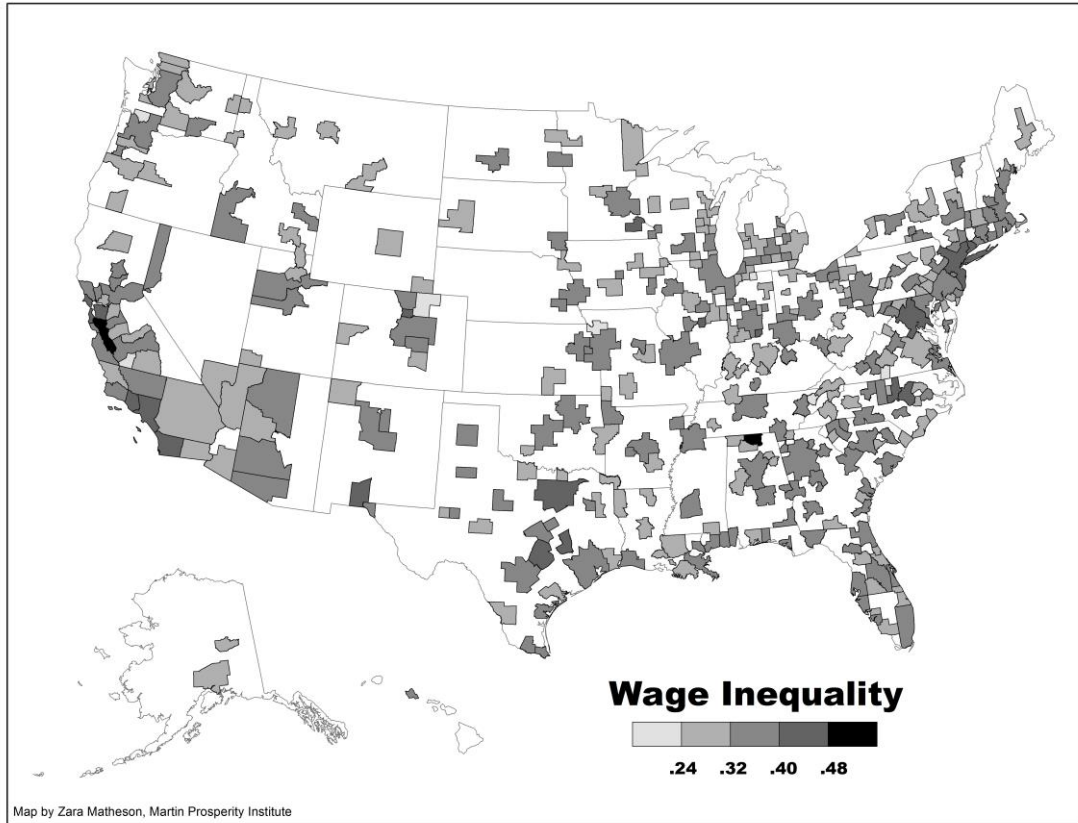**Wage Inequality**
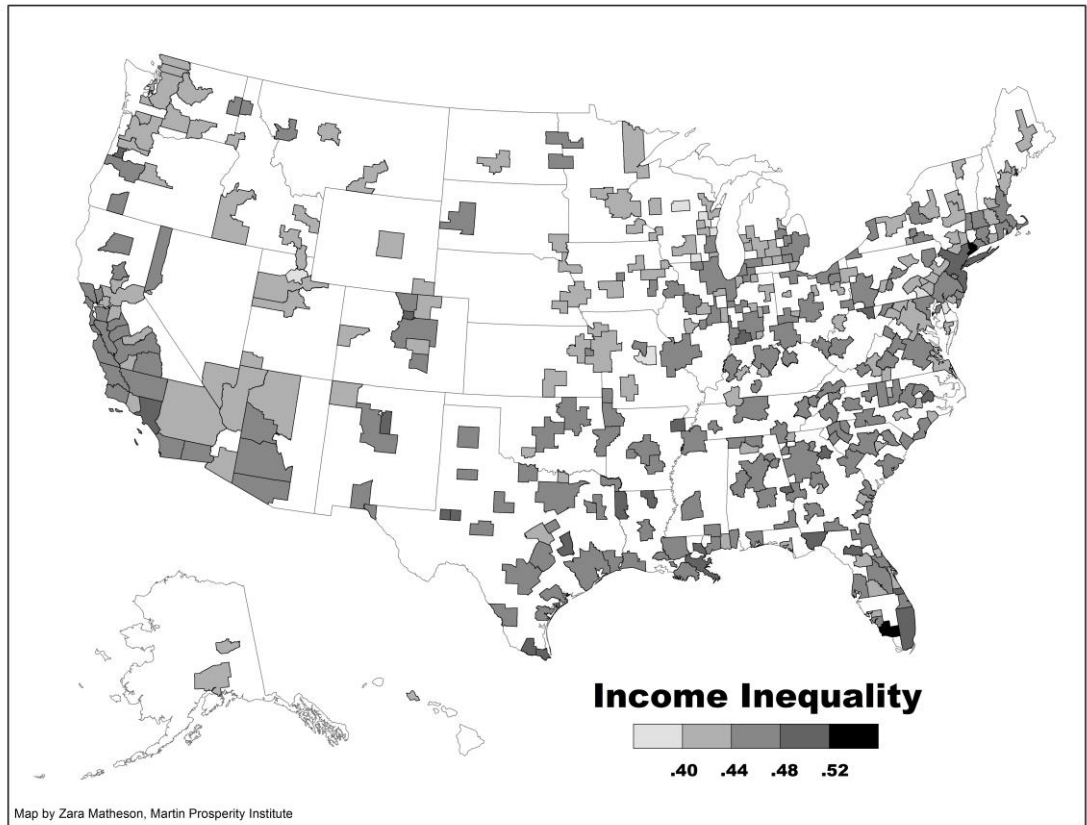
.24 .32 .40 .48

Map by Zara Matheson, Martin Prosperity Institute

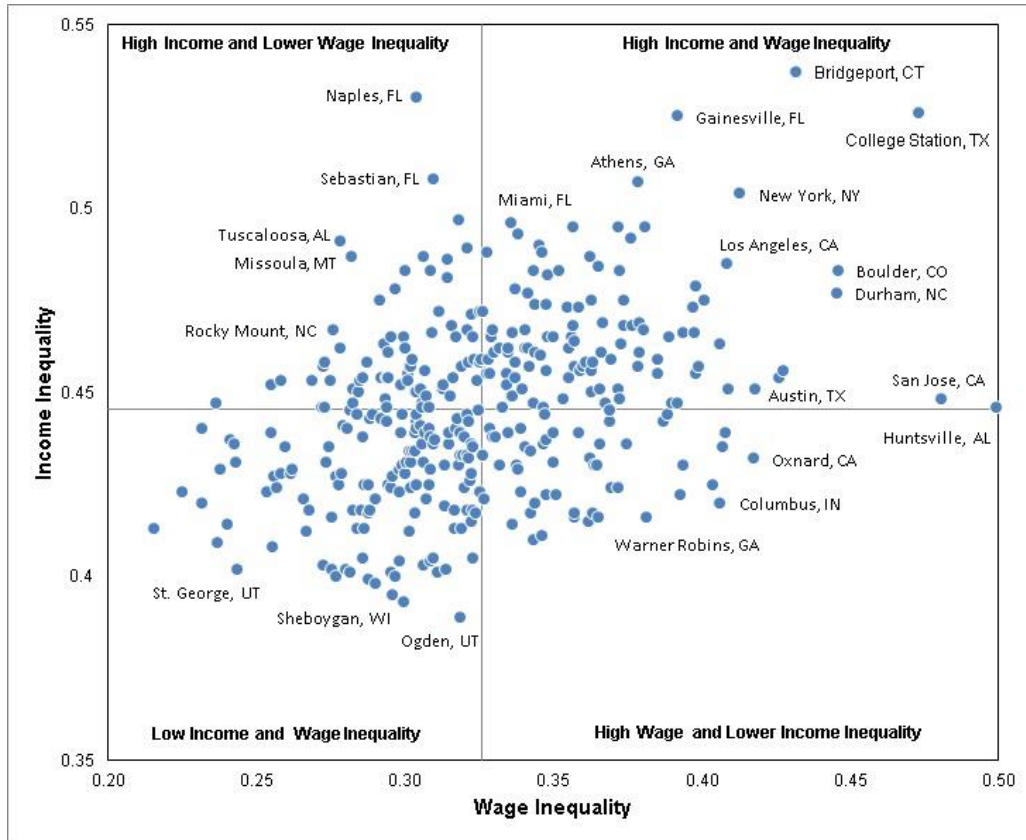**Figure 1:** Wage Inequality

Figure 2: Income Inequality

Figure 3: Wage Inequality vs. Income Inequality
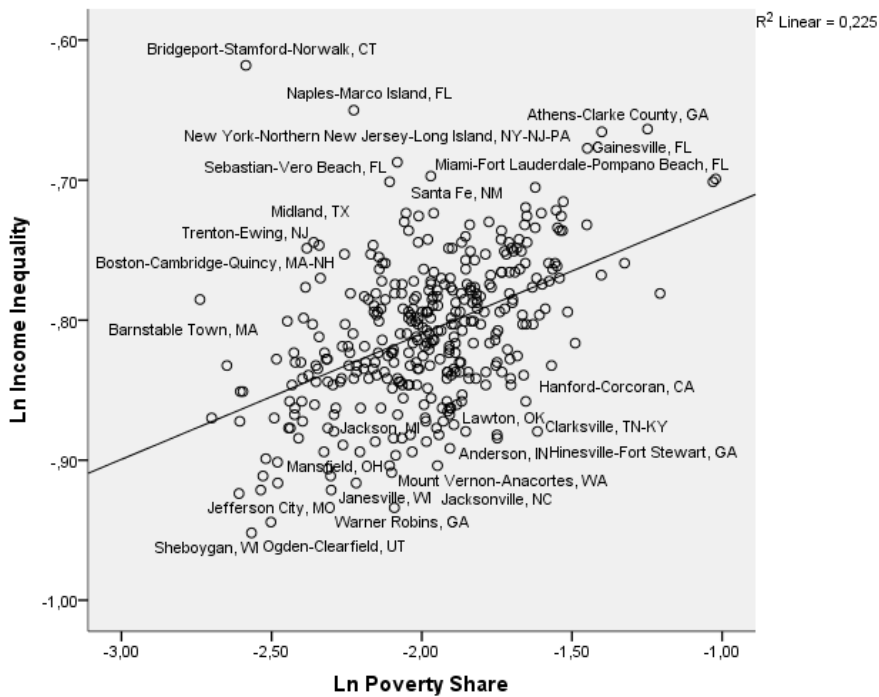

Figure 4: Income Inequalty and Poverty
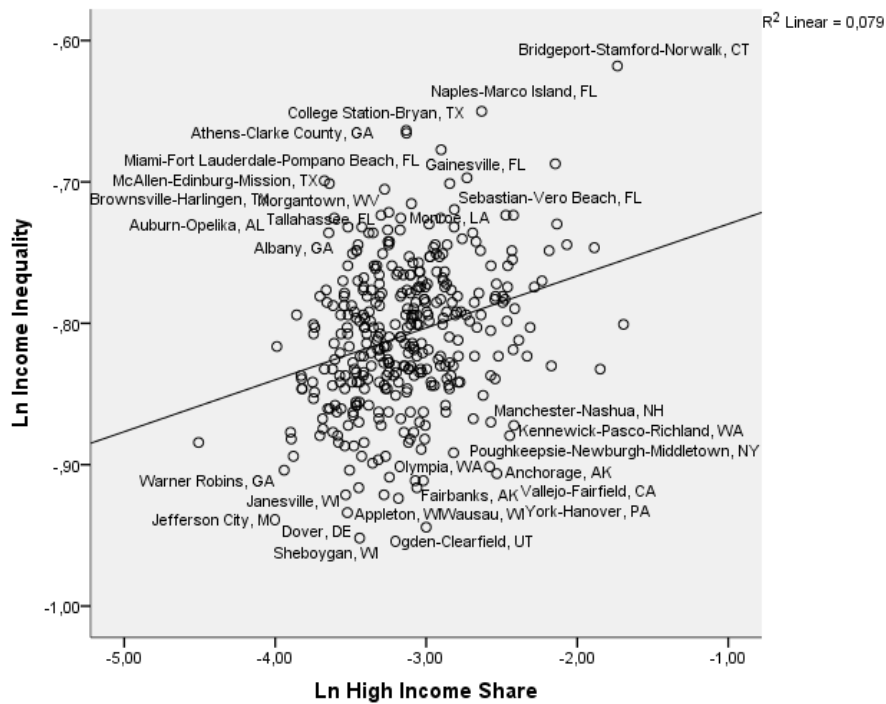
Figure 5: Income Inequality and High Income Share

Table 1: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Income Inequality	359	.386	.539	.446	.024
Wage Inequality	362	.2156	.4996	.326	.044
Average Income	359	13450	44024	240	408
High Technology	359	.00	11.17	.347	1.167
Human Capital	362	.113	.569	.252	.077
Creative Class	359	.171	.484	.299	.047
Analytical Skills*	345	25.26	42.67	32.69	2.391
Social Skills*	345	31.40	46.45	38.20	2.862
Race	362	.00	.50	.105	.107
Metro Size	359	55,262	18,912,644	698,433	1,578,491
Change in Housing Values	360	13,500	356,800	75,817	60,869
Taxation	360	3.87	11.67	6.329	1.112
Unionization	243	.00	35.00	11.19	7.662
Poverty	362	.065	.360	.143	.041
High Income Share	362	.011	.184	.043	.023

*Analytical and social skills are equally weighted and combined into one variable the analysis

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Table 2: Correlation Analysis Findings

	Income Inequality	Wage Inequality
Income Inequality	-	.408***
Wage Inequality	.408***	-
Average Income	.038	.425***
High-Tech	.201***	.625***
Human Capital	.262***	.606***
Creative Class	.188***	.666***
Skills	.210***	.530***
Race	.296***	.201***
Metro Size	.242***	.476***
Taxation	-.233**	-.069
Change in Housing Values	.012	.238***
Poverty	.475***	-.070
High Income Share	.281***	.600***
Unionization	-.336***	-.149**

***indicate significance at the 1 percent level, ** at the 5 percent level.

Table 3: Regressions for Income Inequality and Post-Industrial Structures

Variables	(1)	(2)	(3)	(4)	(5)
Constant	-.627***	-.058***	.439*	-.137	-.137
	(.022)	(.201)	(.246)	(.211)	(.261)
Wage Inequality	.160***	.186***	.156***	.200***	.181***
	(.019)	(.472)	(.025)	(.027)	(.025)
Average Income	-	-.054***	-.100***	-.048**	-.061***
		(-.167)	(.023)	(.020)	(.020)
High Tech	-	.00014*	-.00012	.00086	.00019*
		(.002)	(.002)	(.002)	(.002)
Human Capital	-	-	.049***	-	-
			(.014)		
Creative Class	-	-	-	-.031	-
				(.026)	
Skills	-	-	-	-	.042
					(.052)
N	358	356	356	356	341
R2 Adj	0.164	0.180	0.203	0.181	0.188

**indicate significance at the 1 percent level, **at the 5 percent level, and * at the 10 percent level.

Table 4: Regressions for Income Inequality with Socio-Economic Variables Added

Variables	(6)	(7)	(8)	(9)	(10)
Constant	.017	-1.625***	-2.399***	-1.216***	-1.505***
	(.252)	(.286)	(.256)	(.307)	(.352)
Wage Inequality	.132***	.015***	.065	.063**	.0002
	(.025)	(.019)	(.018)	(.025)	(.023)
Average Income	-.095***	.123***	.207***	-.108***	.112***
	(.024)	(.027)	(.025)	(.027)	(.034)
High Tech	-.011***	-	-	-	-
	(.003)				
Human Capital	.072***	.005	.001	.058***	-.001
	(.014)	(.010)	(.011)	(.013)	(.013)
Race	.010***	.003**	.004**	.010***	.005
	(.002)	(.002)	(.002)	(.002)	(.002)
Metro Size	.014***	-	-	-	-
	(.005)				
Change in Housing Values	.005	-	-	-	-
	(.004)				
Taxation	-.052***	-.040***	-.044***	-.046***	-.028**
	(.014)	(.010)	(.011)	(.013)	(.012)
Poverty	-	.173***	.173***		.176***
		(.010)	(.011)		(.012)
High Income Share	-	.049***	-	.051***	.056***
		(.008)		(.010)	(.009)
Unionization	-				-.007***
					(.002)
N	353	355	355	355	242
R2 Adj.	0.323	.622	.580	.325	.228

***indicate significance at the 1 percent level, **at the 5 percent level, and * at the 10 percent level.