The Geography of Inequality
Differences and Determinants of Wage and Income Inequality across US Metros

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Abstract:

This paper examines the geographic variation in inequality. It distinguishes between two distinct kinds of inequality – wage inequality and income inequality. Wage inequality is closely associated with skills, human capital, technology and metro size - in line with the literature on skill-biased technical change. Income inequality across metros is instead more closely associated with race and poverty as well as with lower levels of unionization and lower tax rates. 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. The two types of inequality are quite different. Wage inequality explains only 16 percent of income inequality across metros, according to our analysis.

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


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
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
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)
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 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 a 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
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 multicollinearity 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.
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
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 to 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, deunionization 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:


FIGURES AND TABLES

Figure 1: Wage Inequality
Figure 2: Income Inequality
Figure 3: Wage Inequality vs. Income Inequality

Figure 4: Income Inequality and Poverty
Table 1: Descriptive Statistics

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*Analytical and social skills are equally weighted and combined into one variable the analysis.
### Table 2: Correlation Analysis Findings

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</table>

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

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

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-.627***</td>
<td>-.058***</td>
<td>.439*</td>
<td>-.137</td>
<td>-.137</td>
</tr>
<tr>
<td></td>
<td>(.022)</td>
<td>(.201)</td>
<td>(.246)</td>
<td>(.211)</td>
<td>(.261)</td>
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<tr>
<td>Wage Inequality</td>
<td>.160***</td>
<td>.186***</td>
<td>.156***</td>
<td>.200***</td>
<td>.181***</td>
</tr>
<tr>
<td></td>
<td>(.019)</td>
<td>(.472)</td>
<td>(.025)</td>
<td>(.027)</td>
<td>(.025)</td>
</tr>
<tr>
<td>Average Income</td>
<td>-.054***</td>
<td>-.100***</td>
<td>-.048**</td>
<td>-.061**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-.167)</td>
<td>(.023)</td>
<td>(.020)</td>
<td>(.020)</td>
<td></td>
</tr>
<tr>
<td>High Tech</td>
<td>-.00014*</td>
<td>.00012</td>
<td>.00086</td>
<td>.00019*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.002)</td>
<td>(.002)</td>
<td>(.002)</td>
<td>(.002)</td>
<td></td>
</tr>
<tr>
<td>Human Capital</td>
<td>-</td>
<td>-</td>
<td>.049***</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(.14)</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Creative Class</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-.031</td>
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<td></td>
<td>-</td>
<td>-</td>
<td>(0.26)</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>Skills</td>
<td>-</td>
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<td>-</td>
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<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.052)</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>358</td>
<td>356</td>
<td>356</td>
<td>356</td>
<td>341</td>
</tr>
<tr>
<td><strong>R2 Adj</strong></td>
<td>0.164</td>
<td>0.180</td>
<td>0.203</td>
<td>0.181</td>
<td>0.188</td>
</tr>
</tbody>
</table>

**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

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

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

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