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

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

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FLORIDA R. and MELLANDER C. The geography of inequality: difference and determinants of wage and income inequality across US metros, *Regional Studies*. This paper examines the geographic variation in wage inequality and income inequality across US metros. The findings indicate that the two are quite different. Wage inequality is closely associated with skills, human capital, technology and metro size, in line with the literature, but these factors are only weakly associated with income inequality. Furthermore, wage inequality explains only 15% of income inequality across metros. Income inequality is more closely associated with unionization, race and poverty. No relationship is found between income inequality and average incomes and only a modest relationship between it and the percentage of high-income households.

Inequality Income Wage High-technology Skills

FLORIDA R. and MELLANDER C. 不均地理：美国各大都会之间薪资与所得不均的差异与决定因素，*区域研究*。本文检视美国各大都会之间薪资不均与所得不均的地理变异。研究发现显示，薪资与所得不均相当不同。与文献相同的是，薪资不均与技术、人力资本、科技及大都会的规模密切相关，但这些因素与所得不均的关係却很薄弱。再者，大都会间的薪资不均仅仅解释所得不均的百分之十五。所得不均与工会化、种族及贫穷较为密切相关。所得不均和平均所得之间并未发现关联，且它和高所得家户的百分比之间儘有微弱的关联。

不均 所得 薪资 高科技 技术

FLORIDA R. et MELLANDER C. La géographie de l'inégalité: les différences et les déterminants de l'inégalité des salaires et des revenus à travers les métropoles aux E-U, *Regional Studies*. Cet article examine la variation géographique de l'inégalité à la fois des salaires et des revenus à travers les métropoles aux E-U. Les résultats indiquent que les deux facteurs sont radicalement différents. L'inégalité des salaires s'associe étroitement aux compétences, au capital humain, à la technologie et à la taille des métropoles, conforme à la documentation. Cependant, ces facteurs-là ne s'associent que faiblement à l'inégalité des revenus. En outre, l'inégalité des salaires explique seulement 15% de l'inégalité des revenus à travers les métropoles. L'inégalité des revenus s'associe plus étroitement à la syndicalisation, à l'origine ethnique et à la pauvreté. Il n'existe aucun rapport entre l'inégalité des revenus et les revenus moyens, et il n'existe qu'un rapport modeste entre l'inégalité des revenus et la proportion des ménages à hauts revenus.

Inégalité Revenu Salaire Haute technologie Compétences

FLORIDA R. und MELLANDER C. Die Geografie der Ungleichheit: Unterschiede und Determinanten der Lohn- und Einkommensungleichheit in verschiedenen Metropolitangebieten der USA, *Regional Studies*. In diesem Beitrag untersuchen wir die geografischen Schwankungen bei der Lohn- und Einkommensungleichheit in verschiedenen Metropolitangebieten der USA. Aus den Ergebnissen geht hervor, dass sich diese beiden Maßstäbe recht stark voneinander unterscheiden. Die Ungleichheit bei den Löhnen steht wie in der Literatur angegeben in engem Zusammenhang mit der Qualifikation, dem Humankapital, der Technologie und der Größe des Metropolitangebiets, doch diese Faktoren hängen nur schwach mit der Einkommensungleichheit zusammen. Darüber hinaus lassen sich durch die Lohnungleichheit nur 15% der Einkommensungleichheit in verschiedenen Metropolitangebieten erklären. Eine Einkommensungleichheit steht in einem stärkeren Zusammenhang mit Gewerkschaftsbildung, Rasse und Armut. Zwischen Einkommensungleichheit und Durchschnittseinkommen wird kein und zwischen Einkommensungleichheit und dem Anteil von Haushalten mit hohem Einkommen nur ein schwacher Zusammenhang festgestellt.

Ungleichheit Einkommen Lohn Hochtechnologie Qualifikationen

FLORIDA R. y MELLANDER C. La geografía de la desigualdad: diferencia y determinantes de las desigualdades salariales y de ingresos en las áreas metropolitanas de los EE.UU., *Regional Studies*. En este artículo analizamos la variación geográfica en la desigualdad de salarios y de ingresos en las áreas metropolitanas de los Estados Unidos. Los resultados indican que estas dos medidas son bastantes diferentes. La desigualdad salarial está estrechamente relacionada con las habilidades, el capital humano, la tecnología y el tamaño del área metropolitana, en consonancia con la bibliografía, pero estos factores están débilmente asociados a la desigualdad de ingresos. Asimismo la desigualdad salarial explica solo el 15% de las desigualdades de ingresos en las áreas metropolitanas. La desigualdad de ingresos está más estrechamente relacionada con la sindicalización, la etnia y la pobreza. No hemos observado ninguna relación entre la desigualdad de ingresos y los ingresos medios y solamente una más bien modesta entre la desigualdad de ingresos y el porcentaje de las familias con ingresos altos.

Desigualdad Ingresos Salario Alta tecnología Habilidades

JEL classifications: J24, O1, O33, R0

INTRODUCTION

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

Today, inequality has once again surged to the fore of popular debate. A large number of economic studies (MURPHY *et al.*, 1998; CARD and DINARDO, 2002; AUTOR *et al.*, 2006) 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 1%, 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 bifurcated. On one side are higher paying, professional, knowledge and creative jobs that require considerable education and skill. And on the other side are an even larger and faster growing number of lower-skill manual jobs in fields such as personal care, retail sales, and food service and preparation that pay much lower wages.

Inequality, according to a large literature, is the product of 'skill-biased technical change' (AUTOR *et al.*, 1998, 2003, 2006). 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-biased technical change and rising inequality.

While the literature on skill-biased technical change emphasizes the polarization of the labour market into high- and low-skill jobs, other studies highlight the rapid growth of low-skill, low-wage jobs in areas of personal services, such as hair care and manicuring, personal and healthcare, retail trade, food preparation and service, which are relatively place-bound and thus harder to move outside the location where they are performed. Such rapidly growing occupations require spatial proximity to the populations and markets they serve and thus cluster around highly affluent populations and areas (MANNING, 2004; GOOS and MANNING, 2007; GOOS *et al.*, 2009). The personalized nature of such low-skill service work reinforces the growth and co-location of high- and low-skill jobs in the same places, underpinning and reinforcing regional wage inequality.

A related literature on job polarization suggests that low- and high-skilled jobs grow in the same regional markets, leading to regional differences in wage inequality (MANNING, 2004; GOOS and MANNING, 2007; GOOS *et al.*, 2009). A number of studies show how large metros have been found to have distinct advantages when it comes to attracting high-skill people, high-technology 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 (FLORIDA, 2002a, 2002b, 2008; BERRY and GLAESER, 2005). Studies by BACOLD *et al.* (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 *et al.* (2009) examined patterns of local-level inequality, they used a modified Gini coefficient and found that there is a connection between urban inequality and the clustering of more 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 metro size and inequality, demonstrating metro size alone accounted for roughly 25–35% of the total increase in economic inequality over the past three decades, after the roles of skills, human capital, industry composition and other factors were taken into account. Moreover, metro size played an ever greater role in explaining the plight of low-wage workers, accounting for 50% more of the increase in inequality for the lower half of the wage distribution than for the upper half.

A large literature in geography, urban studies, sociology and urban economics document the geographic intersection of race and poverty in the United States. WILSON (1990) highlighted the interplay 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 economic growth and poverty reduction. Research by SAMPSON (1995) and SHARKEY (2013) highlights the role of place-based concentrated disadvantage in the perpetuation of poverty over long time scales.

Other studies identify the connection between rising inequality and the unravelling of the post-war social compact between capital and labour. Unionization helped to raise the wages of factory workers and create a larger middle class. Progressive income taxes helped redistribute income, mitigate inequality and bolster the middle class. Both factors vary considerably by location. Unionization rates vary significantly by state. While federal income tax policy creates consistent national rates, rates of state and local taxation vary considerably, and there is a large literature that identifies the effects of such variation on state and local taxes on both firm and household location (BARTIK, 1992, 2002). In the 1980s and 1990s, BLUESTONE and HARRISON (1982, 1986, 1988) identified 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) shows how taxes redistribute incomes and increase the rate at which wealth is equalized. KORPI and PALME (1998) argue that outcomes of market-based distributions are more unequal that those of earnings- and tax-related social insurance programmes. Taken together, de-unionization and lower tax rates reflect the unravelling of the post-war social compact.

This research builds on the literatures described above to shed light on the regional differences in wage and income inequality. While most studies of inequality look at national patterns of inequality over time or across nations, this research focuses on difference in inequality across more than 350 US metro areas. The geographic variation of two types of inequality is examined: wage inequality and income inequality. Do they have a similar geographic structure, or do they differ across regions? An important aspect of this research is to distinguish between these two types of inequality and to probe the regional variation in the factors that bear on each. It is important to note that these two types of inequality are likely to be associated with one another; it is more likely that wage inequality would cause income inequality (a broader category which subsumes wages) rather than the other way around. The geographic determinants of these two types of inequality are also probed by looking at the effects of variables such as human capital and skill, to race, poverty, unionization and tax rates. Each of these variables varies considerably across geography, enabling the relative effects of each to be parsed.

The main findings of this analysis suggest geography plays an important role in shaping inequality. Firstly, it was found that wage inequality and income inequality exhibit different geographic patterns. Across metros, there is little overlap between the two. The geographic variation in wage inequality across US metros accounts for just 16% of the geographic variation in income inequality. Furthermore, the geographic variation of wage inequality and income inequality is found to be explained by different sets of factors. Regional variation in wage inequality, on the one hand, is associated with human capital, skill levels and occupational structure, in line with previous studies of skill-biased change and job polarization. The geographic variation in income inequality, on the other hand, is associated with factors more closely identified with the literature on race and poverty, such as geographic variation in poverty and race as well as regional differences in unionization and tax rates, factors that play at best a modest role in wage inequality.

VARIABLES, DATA AND METHODS

This section now describes the methods, variables and data used in the analysis:

- Income inequality – measured as a Gini coefficient. The variable captures the distribution of incomes from the bottom to the top. Given that the census does not publish individual incomes above US$100 000, the Gini coefficient cannot be calculated. Instead, the three-year estimate of the coefficient provided by the 2010 American Community Survey is used.

- Wage inequality – calculated as a Theil index, which is an entropy measure that 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 wages, a Gini coefficient for wage inequality cannot be calculated, but rather inequality between groups is formulated as a Theil index using 2010 data from the Bureau of Labor Statistics (BLS).
- Average income – 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-technology – a measure of regional concentration of the 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-technology industries, in relation to the nationwide percentage of high-technology industrial output as a percentage of total US high-technology industrial output. These data are from the Census County Business Patterns for 2010.
- Human capital – a measure for the share of the labour force with a bachelor's degree or more taken from the 2010 Census American Community Survey.
- Creative class – 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, healthcare practitioners, technical occupations, and high-end sales and sales management. These data are for the year 2010 from the BLS.
- Skills – 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 (Florida *et al.*, 2011). These data are derived from the O*NET database from the BLS for 2007. For a more detailed description of this score, see Appendix A.
- Race – measures the African-American share of the population; it is derived from the 2010 American Community Survey.
- Metro size – a measure of metro population size for 2010; it is from the Census American Community Survey.
- Change in housing values – a measure of the change in median housing value between 2000 and 2008. These data are from the US Census Bureau.
- Taxation (tax revenue as a percentage of personal income) – the tax revenue as a percentage of personal income by state. These data are for 2007 from US Census.
- Unionization – a measure of the share of employed workers who are union members. Data for 2010 and are from http://unionstats.com/.
- Poverty – measures the share of the population below the poverty line. It is based on data for 2007–09 from the American Community Survey.
- High-income share – measures the share of the population that belongs to the highest income group (US$100 000 and above) for 2007–09 according to the American Community Survey.

Table 1 provides descriptive statistics for these variables.

THE GEOGRAPHY OF WAGE AND INCOME INEQUALITY

This section now turns to the findings from the geographic analysis. To orient the discussion that follows, Figs 1 and 2 and provides maps of the two types of inequality that are the subject of the analysis: wage inequality and income inequality.

Fig. 1 maps the regional variation of wage inequality across US metros. The measure is based on the Theil index, which is an entropy measure that captures differences in wage between occupational groups of knowledge workers, standardized service workers, manufacturing workers, and fishing and farming workers. It is based on 2010 data from the BLS. As shown, wage inequality shows considerable regional variation, ranging from a low of 0.22 to a high more than double that, 0.48–0.50. The metros with the highest wage inequality scores are almost all major high-technology knowledge economy regions such as: Huntsville, Alabama (a centre for semiconductor and high-technology industry); San Jose, California (the fabled Silicon Valley); College Station-Bryan, Texas (home to Texas A&M); Boulder, Colorado (a leading centre for technology start-ups); Durham, North Carolina in the famed Research Triangle, and Austin, Texas (another leading high-technology centre), as well as large, diverse metros such as New York, Los Angeles, greater Washington, DC, and San Francisco – all of which are within the top 20 metros with the most unequal wages.

Table 1. Descriptive statistics

	N	Minimum	Maximum	Mean	Standard deviation
Income inequality	359	0.386	0.539	0.446	0.024
Wage inequality	362	0.2156	0.4996	0.326	0.044
Average income	359	13 450	44 024	240	408
High-technology	359	0.00	11.17	0.347	1.167
Human capital	362	0.113	0.569	0.252	0.077
Creative class	359	0.171	0.484	0.299	0.047
Analytical skills[a]	345	25.26	42.67	32.69	2.391
Social skills[a]	345	31.40	46.45	38.20	2.862
Race	362	0.00	0.50	0.105	0.107
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	0.00	35.00	11.19	7.662
Poverty	362	0.065	0.360	0.143	0.041
High-income share	362	0.011	0.184	0.043	0.023

Note: [a]Analytical and social skills are equally weighted and combined into one variable in the analysis.

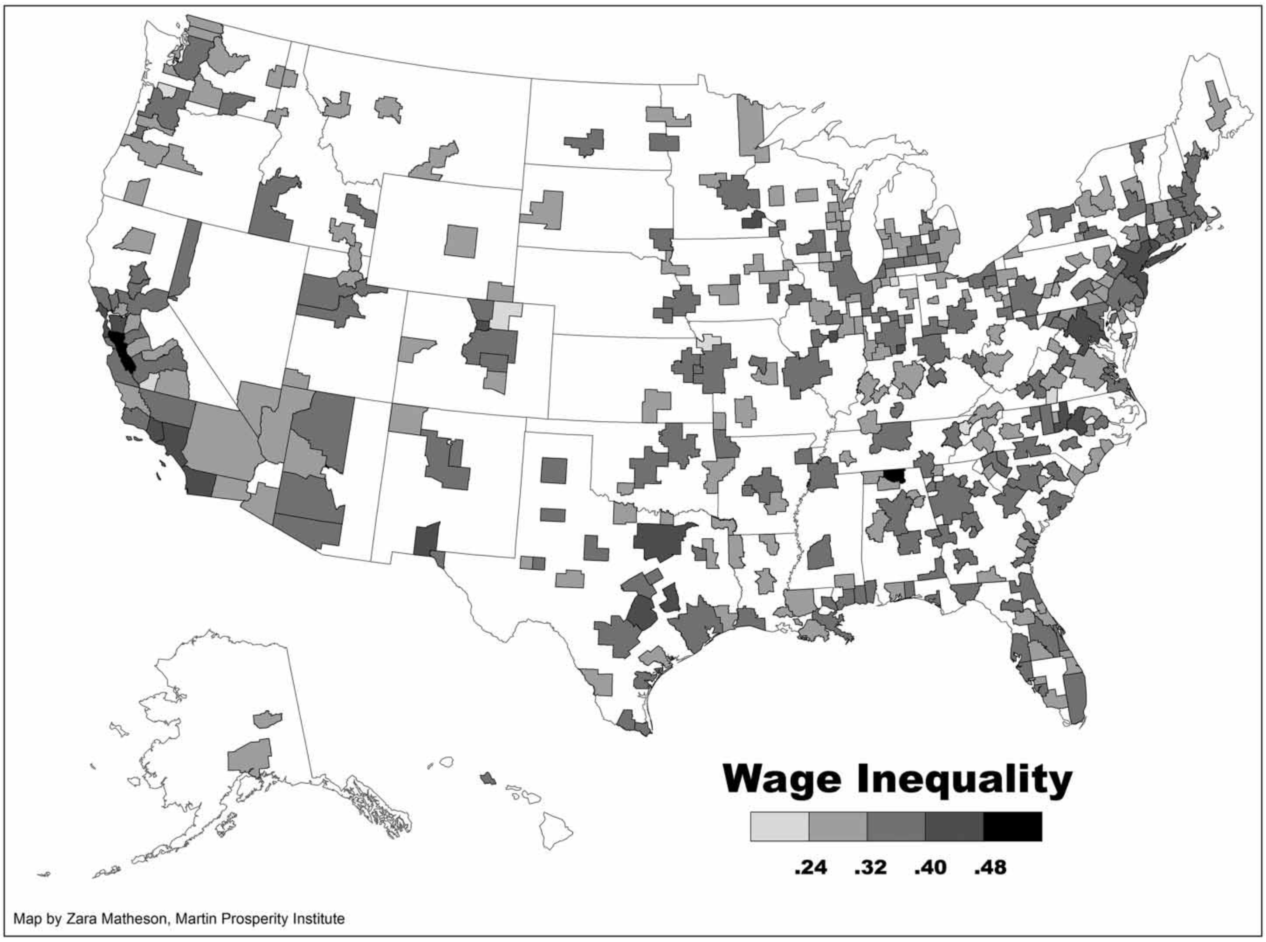

Fig. 1. Wage inequality

Fig. 2 maps the geography of income inequality, measured as a Gini coefficient based on data from the 2010 American Community Survey. The geographic variation is again considerable, ranging from a low of 0.39 to a high of 0.54. But the two maps are far from the same; in fact, they are strikingly different. Knowledge-based high-technology metros do not score highly on income inequality. The most unequal metros are a mix of larger metros, like Bridgeport-Stamford in 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.

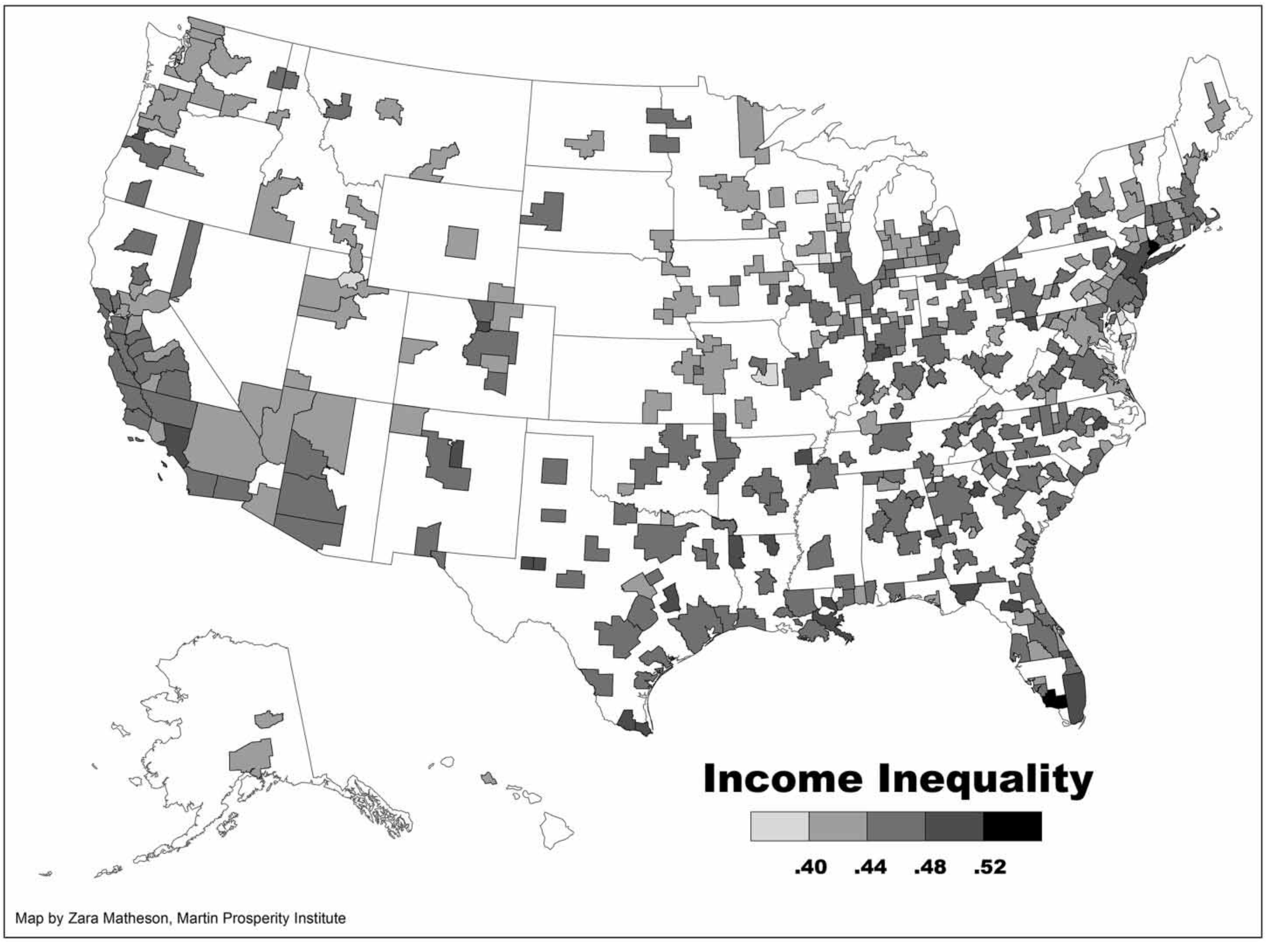

Fig. 2. Income inequality

CORRELATION ANALYSIS

The next step in the analysis is a basic correlation analysis. A start is made by looking at the bivariate relation between the regional variation in wage and income inequality across US metros before turning the wider range of independent variables included in the analysis.

Fig. 3 provides a scatterplot of 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.

Generally, it was found that there are metros with high levels of both wage and income inequality, as well as metros with low levels of both. 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. Thus, a relatively weak association is found between the geographic variation in wage and income inequality.

The section now turns to the correlation findings that compare the geographic variation in wage and inequality with variables that the literature suggests are likely to affect this geographic pattern. Table 2 summarizes the basic results of the correlation analysis.

The correlation between these two types of inequality across more than 350 metros is 0.408. This is a moderate but not overwhelming level of association. While the two are associated across geography, one does not fully explain the other. In other words, the geographies of wage and income inequality have at best a modest degree of overlap.

Beyond this, the key results of the correlation analysis point to a number of interesting geographic patterns and especially to differences between the two types of inequality.

A start is made with the factors that might potentially relate to wage inequality. The geographic variation in wage inequality is significantly associated with factors identified in the literatures on skill-biased technical change and job polarization: human capital (0.606), knowledge-based and creative occupations (0.666), high-technology industry (0.625), and analytical and

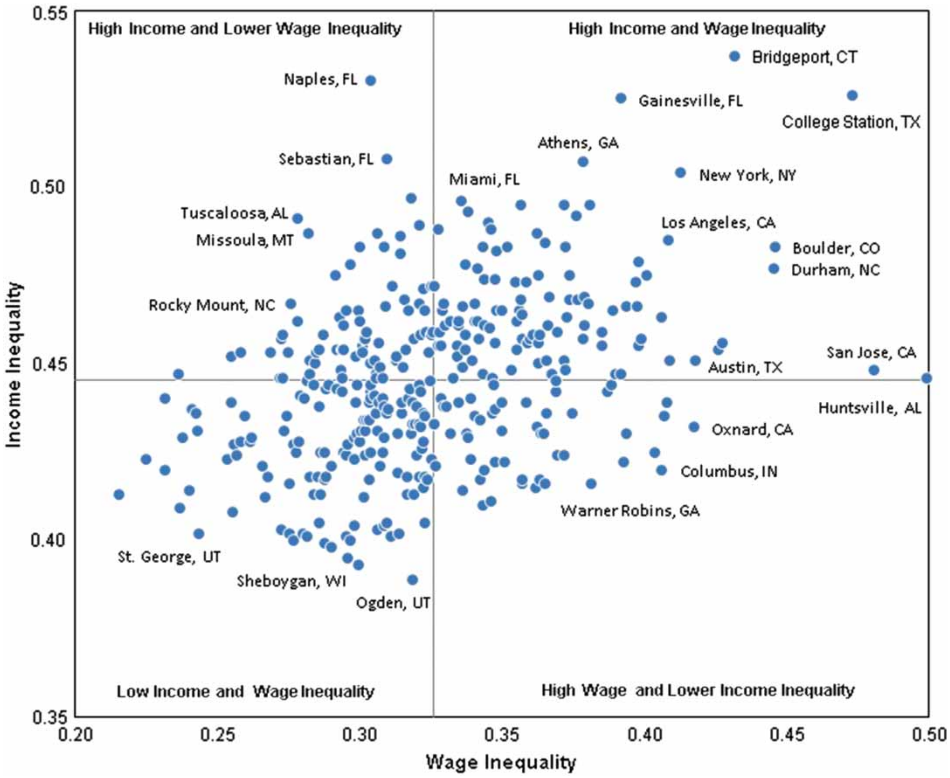

Fig. 3. Wage inequality versus income inequality

Table 2. Correlation analysis findings

	Wage inequality	Income inequality
Income inequality	0.408***	–
Wage inequality	–	0.408***
Average income	0.425***	0.038
High-technology	0.625***	0.201***
Human capital	0.606***	0.262***
Creative class	0.666***	0.188***
Skills	0.530***	0.210***
Race	0.201***	0.296***
Metro size	0.476***	0.242***
Taxation	−0.069	−0.233**
Change in housing values	0.238***	0.012
Poverty	−0.070	0.475***
High-income share	0.600***	0.281***
Unionization	−0.149**	−0.336***

Note: ***Significance at the 1% level; and **significance at the 5% level.

social skills (0.530). Wage inequality is also associated with high-income share (0.600), average income levels (0.425), and metro size (0.476). Geographic variation in wage inequality is not significantly associated with poverty or taxation, and only modestly associated with race (0.201), change in housing values (0.238), and unionization (–0.149).

This section now turns to the factors that might potentially correlate with the geographic variation in income inequality. The differences in the factors associated with the two types of inequality are immediately apparent. Regional variation in income inequality is more closely related to race, poverty and indicators of the unravelling of the social compact (de-unionization and lower rates of taxation). It is most closely associated with poverty (0.475) and slightly less so to race (0.296). It is negatively associated with unionization (–0.336); in other words inequality is higher in metros with lower levels of unionization; and it is also negatively associated with taxation (–0.233), as inequality is higher in metros with lower rates of taxation. The geographic variation in income inequality is modestly associated with some of the factors identified in the literatures on skill-biased technical change and job polarization such as: human capital (0.262), the high-income share of the population (0.281), metro size (0.242), workforce skill (0.210), high-technology industry (0.201), and knowledge and creative occupations (0.188). It is not significantly associated with average income or changes in housing values.

To a certain degree, the associations between income inequality and high degrees of poverty, on the one hand, and high degrees of affluence, on the other, should not be surprising. Income inequality, measured by the Gini coefficient, captures the income distribution from bottom to 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 by the higher part of the Lorenz curve (which is used to estimate the Gini). However, if incomes in general are high within 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.

That said, the actual pattern is found to be mixed. There are some regions that have low shares of poverty combined with relatively high levels of income inequality, e.g. Bridgeport, Naples, New York, Miami, Boston and San Francisco. There are other metros with low levels of income inequality, but with relatively high shares of poverty (e.g. Hanford in California, Clarksville in Tennessee-Kentucky, and Hinesville in Georgia). At the same time there are metros 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. As Table 2 shows, the correlation between income inequality and the share of high-income households is insignificant (–0.070), while the correlation between income inequality and poverty is positive and significant (0.475). This suggests that income inequality is more related to the bottom of the socio-economic order than to the top of it.

MULTIPLE REGRESSION ANALYSIS

To further understand the geographic variation and regional determinants of wage and income inequality, this section turn to the results of the multiple regression analysis. The model is estimated by a basic ordinary least squares (OLS) regression with inequality as the dependent variable and a series of independent variables. The models are formulated based on the assumption that wage inequality affects income inequality, not the other way around. The first set of models are designed to test the explanatory power of different variables related to the literatures on skill-biased technical change and job polarization, such as skills and high-technology industry shares on the regional variation of both wage and income inequality. Socio-economic variables are then added such as average income, race, changes in housing values, income taxation rates, poverty shares, high-income shares, unionization, and a control for metro size to the income inequality model to compare their relative strength with the first set of skill-biased technical change and job polarization variables. Socio-economic variables are only included in the income inequality regression since the correlation analysis suggests weak associations between them and the geography of wage inequality. However, the R^2 adjusted values for wage inequality regressions with socio-economic variables included are run and reported in order to evaluate to what extent these socio-economic variables add to the explanatory power of these regressions. All variables are in logged form, and the coefficients can be interpreted as elasticities. Since a certain degree of multicollinearity would be expected between the explanatory variables, a full correlation matrix is included in Table B1 in Appendix B. The variance inflation factor (VIF) values are also reported separately in relation to the analysis.

A start is made with the regressions for wage inequality. Table 3 summarizes the key results from the regressions where wage inequality as well as income inequality can be explained by variables related to technical change. Due to multicollinearity issues, models of the three skills variables (human capital, creative class and skills) were run one at a time. The top of Table 3 includes the wage inequality regressions, while the bottom illustrates the income inequality regression results.[1]

Equation (I1) (bottom of Table 3) models the basic relationship between wage inequality and income inequality alone, based on the assumption that income inequality is a function of wage inequality. Wage inequality, while significant, explains just 16% of the variation in income inequality across regions.

Equation (2) adds two additional variables: average income and high-technology. In the wage inequality regression (W2), both high-technology and average income are significant and the R^2 value is close to 0.4. In the income inequality regression (I2) the R^2 adjusted increases just slightly compared with in W1, to 0.180. High-technology is weakly significant. 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. Also, if the R^2 generated from regression W2 and I2 (without wage inequality for comparison reasons) is compared, a major difference is found. While W2 has an R^2 of 0.40, the R^2 of regression I2 is only 0.05, suggesting that income inequality is significantly less explained by these variables than wage inequality. Even when wage inequality is included in the regression, the explanatory power is significantly lower than in regression W2.

Equation (3) adds human capital, measured as the percentage of adults with at least a college degree or above. In the wage inequality regression (W3), human capital as well as high-technology is significant, and the R^2 adjusted increases by 0.065 to 0.457. In the income inequality regression (I3), the R^2 adjusted increases slightly to 0.203. While human capital is positive and significant, the included variables still explain significantly less than in the wage inequality regression. Wage inequality and average income remain significant, while high-technology concentration loses its significance in the income inequality regression (I3).

Table 3. Regressions for wage inequality and income inequality and post-industrial structures

Variables	(W1)	(W2)	(W3)	(W4)	(W5)
Wage inequality regression (W)					
Constant	–	−0.587***	0.456	−0.294	−2.932***
		(0.432)	(0.513)	(0.419)	(0.545)
Average income	–	0.058*	−0.122**	−0.027	0.031
			(0.048)	(0.039)	(0.044)
		(0.042)			
High-technology	–	0.039***	0.029***	0.023***	0.030***
		(0.003)	(0.004)	(0.004)	(0.004)
Human capital	–	–	0.185***	–	–
			(0.028)		
Creative class	–	–	–	0.403***	–
				(0.046)	
Skills	–	–	–	–	0.444***
					(0.111)
N	–	356	356	356	341
R^2	–	0.395	0.462	0.503	0.412
R^2 adjusted	–	0.392	0.457	0.499	0.407

Variables	(I1)	(I2)	(I3)	(I4)	(I5)
Income inequality regressions (I)					
Constant	−0.627***	−0.058***	0.439*	−0.137	−0.137
	(0.022)	(0.201)	(0.246)	(0.211)	(0.261)
Wage inequality	0.160***	0.186***	0.156***	0.200***	0.181***
	(0.019)	(0.472)	(0.025)	(0.027)	(0.025)
Average income	–	−0.054***	−0.100***	−0.048**	−0.061***
		(−0.167)	(0.023)	(0.020)	(0.020)
High-technology	–	0.00014*	−0.00012	0.00086	0.00019*
		(0.002)	(0.002)	(0.002)	(0.002)
Human capital	–	–	0.049***	–	–
			(0.014)		
Creative class	–	–	–	−0.031	–
				(0.026)	
Skills	–	–	–	–	0.042
					(0.052)
N	358	356	356	356	341
R^2 adjusted	0.164	0.180	0.203	0.181	0.188
R^2 (without wage inequality)	–	0.052	0.118	0.062	0.072
R^2 adjusted (without wage inequality)	–	0.046	0.111	0.054	0.063

Notes: **Significance at the 1% level; **significance at the 5% level; and *significance at the 10% level.

All independent variables generate VIF values below 3, which indicates that the models do not suffer from multicollinearity to any large extent.

Equation (4) substitutes the variable for human capital with that of the creative class. In the wage inequality regression (W4), the creative class and high-technology variables remain significant. The R^2 adjusted increases even further to 0.457, suggesting that almost 50% of the variation in wage inequality is explained by the included variables. For the income inequality regression (I4), the pattern is still different. The R^2 adjusted is even lower than in I3 (now down to 0.188), and if the R^2 values in W4 and I4 (when wage inequality is excluded for comparison reasons) are compared, the difference is a striking 0.441 (0.503 compared with 0.054). The occupation variable is insignificant in I4, indicating that income inequality is not related to higher shares of creative class workers, once wage inequality and average income have been controlled for.

Equation (5) substitutes the skill variable leading to similar insignificant results; in other words, skills is significantly related to wage inequality (W5) but insignificant in relation to income inequality (I5).

Overall, the results suggest that the geographic variation in wage inequality is significantly more related to skill-biased technical change variables such as high-technology and different forms of skill, while income inequality is significantly less so. A modest association with average income levels, human capital and to some extent high-technology industry is found. Creative class occupations and underlying workforce skills are insignificant once wage inequality, average income and high-technology are controlled for.

Based on this, the paper proceeds with the next step in the regression analysis, adding the socio-economic variables and measures identified in the literatures on race, poverty and de-unionization. Table 4 reports the key findings. In addition to adding socio-economic variables such as race, poverty and high-income share, measures

Table 4. Regressions for wage and income inequality with socio-economic variables added

Variables	(6)	(7)	(8)	(9)	(10)
Income inequality regressions (I)					
Constant	0.017	−1.625***	−2.399***	−1.216***	−1.505***
	(0.252)	(0.286)	(0.256)	(0.307)	(0.352)
Wage inequality	0.132***	0.015***	0.065	0.063**	0.0002
	(0.025)	(0.019)	(0.018)	(0.025)	(0.023)
Average income	−0.095***	0.123***	0.207***	−0.108***	0.112***
	(0.024)	(0.027)	(0.025)	(0.027)	(0.034)
High-technology	−0.011***	–	–	–	–
	(0.003)				
Human capital	0.072***	0.005	0.001	0.058***	−0.001
	(0.014)	(0.010)	(0.011)	(0.013)	(0.013)
Race	0.010***	0.003**	0.004**	0.010***	0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Metro size	0.014***	–	–	–	–
	(0.005)				
Change in housing values	0.005	–	–	–	–
	(0.004)				
Taxation	−0.052***	−0.040***	−0.044***	−0.046***	−0.028**
	(0.014)	(0.010)	(0.011)	(0.013)	(0.012)
Poverty	–	0.173***	0.173***	–	0.176***
		(0.010)	(0.011)		(0.012)
High-income share	–	0.049***	–	0.051***	0.056***
		(0.008)		(0.010)	(0.009)
Unionization	–	–	–	–	−0.007***
					(0.002)
N	353	355	355	355	242
R^2 adj.	0.323	0.622	0.580	0.325	0.640
R^2 (without wage inequality)	0.267	0.629	0.572	0.324	0.652
R^2 adjusted (without wage inequality)	0.252	0.622	0.566	0.314	0.641
R^2 and R^2 adjusted generated from equivalent wage regressions					
R^2	0.492	0.531	0.431	0.520	0.548
R^2	0.482	0.523	0.423	0.513	0.535

Note: ***Significance at the 1% level; **significance at the 5% level; and *significance at the 10% level. Equation (6) indicates a strong multicollinearity for High-technology and Metro size, with VIF values of 6.3 and 4.6. All other VIF values are below 3. There is also a strong correlation between average income and poverty, which most probably is causing the shifting sign of the average income coefficient.

of unionization, taxation and housing values should also be added, while excluding a number of variables that were insignificant in the analysis above. A control variable for metro size is also added to examine the possible connection between metro size and inequality. R^2 values for wage inequality regressions are reported below to see to what extent they increase when socio-economic variables are added to the model.[2]

Equation (6) introduces race, change in housing values, taxation and metro size. This doubles the R^2 adjusted values to 0.323, 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 a strong collinearity is expected between these variables, VIF values were also generated, which indicate that there is a relatively strong association between high-technology and metro size. Equation (6) was rerun and high-technology and metro size were included one at a time. When run individually, each variable also turned out to be insignificant. Additionally an interaction variable was created for high-technology and metro size, and it was also insignificant in this model. Both variables were therefore excluded in the following regressions.

Equation (7) has poverty and the share of high-income households added. Studies by GORDON and DEW-BECKER (2008) and DEININGER and SQUIRE (1996) have demonstrated the consequences of poverty on levels of inequality. 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 the model (and increase the R^2 values), they are added to the model in combination, as well as one by one. Both variables as expected are significant. 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 income inequality more than the share of people with high incomes. Wage inequality, race and taxation rates all remain significant.

Equation (8) only includes poverty and equation (9) only includes high-income share in order to be parse the relative effects of each. The regression with poverty generates an R^2 adjusted of 0.580, substantially higher than that R^2 of 0.325 for the regression with the high-income share variable. Note that the variable for high-income share is limited by the fact that the cut-off is US\$100 000 (based on the definition from the census), and as a result the exact slope of the Lorenz curve cannot be determined. That said, the findings still suggest income inequality is more strongly related to poverty, in other words with the bottom end of the income distribution than with the top end of it.

In the last model, equation (10) includes the unionized share of the labour force. Including it reduces the sample by one-third due to lack of data and this may have an effect on the estimations overall. The variable for unionization is negative and significant. In other words, unionization has a dampening effect on income inequality across metros regions. Average income remains significant in this model, but human capital does not. When one checks for multicollinearity, relatively high VIF values are found between average income and human capital. To understand this better, income and human capital were run separately. Now each variable is significant. A single interaction term was then created from both the income and human capital variables, and it remained significant. Thus, it can be concluded that human capital remains associated with income inequality and that the insignificant sign is a result of multicollinearity in the model. Equation (10) was also rerun with the smaller sample, but without the unionization variable. Wage inequality, human capital and race remained insignificant. Therefore, it is concluded that the insignificance of these values in equation (10) is due to the reduced sample size rather than to the inclusion of the unionization variable.

The equivalent regressions for wage inequality were also rerun for comparison reasons. The generated R^2 and R^2 adjusted values can be found at the bottom of Table 4. In general, adding the socio-economic variables adds little to the explanatory power of the model (cf. the results with Table 3 above). The R^2 adjusted values are significantly lower when only poverty is included in the model (0.423) (regression 8), and the R^2 adjusted value increases by almost 0.1 (to 0.513) (regression 9), when high-income shares are included instead. This suggests that the geographic variation of wage inequality is more sensitive to the top of the income distribution in comparison with the geographic variation in income inequality that is more sensitive to the bottom.

DISCUSSION AND CONCLUSIONS

This research has examined the geographic variation in inequality across the United States. It distinguished between two distinct types of inequality: wage and income inequality. The geographic variation in each was mapped and charted across US metros and the results presented of the correlation and regression analysis examining factors that the literatures on skill-biased technical change and job polarization, on the one hand, and on race, class and poverty, on the other, suggest are associated with inequality.

Perhaps the most striking finding of the analysis is found when looking at the data geographically, that is across US metros: these two types of inequality turn out to be only modestly correlated with one another: Wage inequality explains 16% of the variation in income inequality across US metropolitan regions.

The two types of inequality are also associated with very different regional clusters of variables, according to the analysis. The geographic variation in wage inequality is most closely associated by the factors identified in the literatures on skill-biased technical change and job polarization. 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-technology industry. The geography of wage inequality is also more driven by the top of the income distribution than by poverty. Furthermore, while the literatures on skill-biased technical change and job polarization suggest that high- and low-skilled jobs grow in the same locations, the findings indicate that this does not necessarily imply higher levels of income inequality.

The geographic variation in income inequality is less closely associated with the factors identified by studies of job polarization and skill-biased technical change. Regional variation in income inequality is more closely associated with the geography of poverty and race (WILSON, 1990) as well as de-unionization (BLUESTONE and HARRISON, 1988), and low tax rates. This is reinforced by the finding that income inequality tends to be negatively associated with average incomes, which suggests that more affluent metros on average are not necessarily more unequal. It is also found that regional variation in income inequality is more closely associated with the geographic variation in poverty than with geographic variation in extreme affluence. It can therefore be concluded that the geographic variation in income inequality across US metros is more of a consequence of the sagging taking place at the bottom of socio-economic order.

Metro size is closely related to wage inequality, but not associated with income inequality when one controls for other socio-economic variables. The geographic sorting of the population across human capital and skill groups that plays such a large role in wage inequality does not appear to play much of a role, if any, in the incidence of income inequality across metros.

For these reasons, it is suggested that future research focuses on the differences and distinctions between these two kinds of inequality. While much of the current literature focuses on the effects of skill-biased technical change and job polarization, the findings are reminiscent of the ongoing role of race and poverty as well as the unravelling of the post-war social compact in the geography of in income inequality.

The best assessment based on the findings of this research is that skill-biased technical change and job polarization are a necessary but insufficient condition to explain the geography of income inequality across US metros. The enduring legacy of and geographic variation in race and poverty and the differential geographic unravelling of the post-war social compact reflected in de-unionization and low tax rates also play significant roles. Thus, policy measures designed to address income inequality should deal with all these factors. Most of all, it is hoped this research and findings spur additional research on the geographic causes and consequences of inequality.

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APPENDIX A: THE SKILLS VARIABLE

Work by FLORIDA *et al.* (2011) is built on to calculate the skills variable. A start is made by measuring the skill value for each occupation. It is based on the O*NET database developed for the US Department of Labor and contains detailed analysis conducted by occupational specialists, occupational analysts and job incumbents. They quantify how much of a certain 'skill' is required for each of 728 occupations, resulting in 87 identified skill variables. Exploratory cluster analysis is used to categorize these 87 skill variables in three distinct groupings: analytical skills, social intelligence skills and physical skills.

Once the groups were identified through cluster analysis, the skill scores were created. The 87 'skill' and 'ability' variables, as defined by O*NET, measure various dimensions of occupational requirements. Each variable has two components: importance (on a 1–5 scale) and level (on a 0–7 scale). The scales were multiplied together to obtain a single measure for each variable, and then the percentile rank across all occupations was taken. To generate the skill scores employed in the analysis, the occupational skill percentile was taken and weighed by employment share in each occupation for each region. The score for a region indicates the average skill percentile across all occupations. The data are a combination of the O*NET data and Bureau of Labor Statistics (BLS) data for occupations.

This analysis includes a combination of analytical and social skills, equally weighted. Analytical skills mainly consist of a numerical facility, and general cognitive functioning, involving skills such as developing and using rules and methods to solve problems. Social skills have a personal element and are related to skills such as understanding, collaborating with and managing other people. The correlation between analytical skills is reasonably high, with a correlation coefficient of 0.694. Because of this, the social and analytical variable is converted into a single variable through a principal component analysis, where the generated social analytical measure variable correlate with the analytical score variable with 0.903 and the social score variable with 0.934.

APPENDIX B

Table B1. *Correlation matrix*

	Average income	High-technology	Human capital	Creative class	Skills	Race	Metro size	Taxation	Change in housing values	Poverty	High-income share	Unionization
Average income	1	0.602**	0.737**	0.548**	0.510**	−0.004	0.417**	0.098	0.526**	−0.725**	0.783**	0.132*
High-technology	0.602**	1	0.662**	0.672**	0.648**	0.145**	0.845**	−0.051	0.398**	−0.360**	0.732**	0.105
Human capital	0.737**	0.662**	1	0.749**	0.500**	−0.062	0.403**	0.012	0.419**	−0.353**	0.648**	0.001
Creative class	0.548**	0.672**	0.749**	1	0.631**	0.100	0.457**	0.014	0.282**	−0.184**	0.564**	0.161*
Skills	0.510**	0.648**	0.500**	0.631**	1	0.198**	0.538**	−0.042	0.095	−0.271**	0.564**	0.002
Race	−0.004	0.145**	−0.062	0.100	0.198**	1	0.276**	−0.127*	−0.230**	0.176**	0.100	−0.193**
Metro size	0.417**	0.845**	0.403**	0.457**	0.538**	0.276**	1	−0.071	0.338**	−0.224**	0.641**	0.106
Taxation	0.098	−0.051	0.012	0.014	−0.042	−0.127*	−0.071	1	0.156**	−0.136**	0.010	0.299**
Change in housing values	0.526**	0.398**	0.419**	0.282**	0.095	−0.230**	0.338**	0.156**	1	−0.430**	0.607**	0.199**
Poverty	−0.725**	−0.360**	−0.353**	−0.184**	−0.271**	0.176**	−0.224**	−0.136**	−0.430**	1	−0.487**	−0.191**
High income share	0.783**	0.732**	0.648**	0.564**	0.564**	0.100	0.641**	0.010	0.607**	−0.487**	1	0.082
Unionization	0.132*	0.105	0.001	0.161*	0.002	−0.193**	0.106	0.299**	0.199**	−0.191**	0.082	1

Note: **Significance at the 1% level; and *significance at the 5% level.

NOTES

1. A test was also conducted for two alternative measures for industry mix: manufacturing share and the share of education and healthcare sector employment (this variable can also serve as a proxy for governmental share of employment). The results were similar to the high-technology variable. Both variables were more closely related to wage inequality than income inequality. These industry-mix variables, however, generated severe multi-collinearity problems when integrated in the current models. Also, when the high-technology variable was substituted for the manufacturing and education and healthcare variables, these new variables became insignificant once skills were controlled for.
2. The wage inequality regressions are slightly different than the income inequality regressions, since it is not assumed that wage inequality is a function of income inequality. R^2 values are reported without wage inequality in Table 4 to compare across the two sets of regressions.

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