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Alicia Cavanaugh and Sébastien Breau

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Article abstract

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CHANGING FORTUNES: AN ANALYSIS OF THE DYNAMICS OF INCOME INEQUALITY IN US METROPOLITAN AREAS

Alicia Cavanaugh, Sébastien Breau

Alicia Cavanaugh
Department of Geography
McGill University
805 Sherbrooke St. West
Burnside Hall (Room 720)
H3A 0B9
alicia.c.cavanaugh@gmail.com

Sébastien Breau
Department of Geography
McGill University
805 Sherbrooke St. West
Burnside Hall (Room 720)
H3A 0B9
sebastien.breau@mcgill.ca

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Abstract:
Income inequality has increased significantly in OECD countries over the last few decades. Rising inequality has been particularly pronounced in the United States, especially so in metropolitan areas. During this time, the increasingly uneven distribution of income reflects the pulling away of high-income earners, as well as increased returns to skilled workers. This study uses IPUMS data to build a novel dataset for 226 MSAs over the 1980 to 2010 period. Results suggest that education has had the strongest impact on rising inequality across US metropolitan areas. Our findings also suggest that supply-side factors such as racial segregation and the size of the immigrant population are likewise positively linked with greater inequality.

INTRODUCTION

Income inequality has increased substantially in recent decades, especially within developed nations. Evidence of rising inequality first emerged in the US and the UK in the late 1970s and early 1980s, a pattern soon followed by most other OECD nations (OECD, 2011). In the United States, the increase in inequality has been especially severe; by the time of the Great Recession of 2008-09, American income inequality had reached levels not seen since the late 1920s (Piketty, 2014).

With inequality worsening, researchers have placed greater attention on understanding the conditions that produce it, as well as its consequences (Cavanaugh & Breau, 2018). Among other things, rising inequality has been linked to greater economic and political instability, and is seen as one of the greatest social challenges of our time (Galbraith, 2012; Stiglitz, 2012; Essletzbichler & al., 2018; Rodriguez-Pose, 2018).

While US inequality has oft been examined at national- and broader regional scales, less attention has been paid to its dynamics across metropolitan regions. This paper follows in the steps of analyses that examine the economic, social, and institutional determinants of metropolitan-level inequality, expanding on the topic by providing a more up-to-date and longer time series perspective to changes in inter-metropolitan inequality in the US (Chakravorty, 1996; Silver & Bures, 1997; Glaeser & al., 2009; Bolton & Breau, 2012; Wallace & al., 2012; Essletzbichler, 2015; Berube & Holmes, 2016).

We do so by developing a novel dataset of metropolitan characteristics in the US over the 1980 to 2010 period. This dataset is then used to pursue two objectives: 1) examine how trends in metropolitan income inequality have changed over a long period of time, and 2) explore the factors that have influenced these patterns. From a modelling perspective, the long-term effects of inter-metropolitan income inequality are examined using pooled OLS regression analysis, while fixed effects models are used to examine how changing metropolitan characteristics impact metropolitan inequality over the short-term (Marchand & al., 2017). Additionally, multiple measures of inequality (sensitive to different parts of the income distribution) are employed to further examine how specific factors affect different parts of the income distribution, lending itself to a more robust understanding of how income inequality has changed over time. This paper incorporates a number of determinants of inequality into the model, which also fills a gap in the literature where they are often examined separately. Of the studies that incorporate a broad range of determinants, many are cross-sectional analyses or time-series based on older data (Baum-Snow & Pavan, 2013; Chakravorty, 1996; Fallah & al., 2011; Florida & Mellander, 2014; Wallace & al., 2012). This study uses the most recent census data and adopts a multi-dimensional conceptual framework.

Within the metropolitan context, inequality is shaped by the uneven and highly concentrated process of urban development (Smets & Salman, 2008). In the US, certain metropolitan areas are experiencing significant economic growth, whereas others are on the decline. Nationally, how and where inequality manifests itself depends on the outcomes of economic processes that are shaped by varied and various economic, social and environmental influences. MSAs are representative of labour market geographies that stretch beyond central city boundaries, making metropolitan areas an ideal unit to examine individual and household economic outcomes within similar economic contexts (Madden, 2000). Beyond their role as a market proxy, MSAs are also useful in studying income inequality because they represent an environment where people live in close-proximity to each other and can compare outcomes and conditions of those living nearby (Madden, 2000). This spatial unit of analysis therefore places inequality locally, which is not only pertinent for policy makers, but also more broadly for those concerned about fairness and justice in their own community to see how economic outcomes vary amongst their neighbors.

Overall, we find that US metropolitan income inequality has increased significantly since 1980. And while upper-tail total income inequality metrics decreased slightly in 2010, wage inequality measures continued to grow post-recession. In terms of the determinants of these patterns, greater educational attainment is the factor most consistently related to income inequality. The extent of segregation and the size of the immigrant population are also consistently linked to inequality. Development is positively related to inequality, while unemployment and other socio-demographic variables show mixed effects. Institutional factors are less able to prevent the rise in inequality.

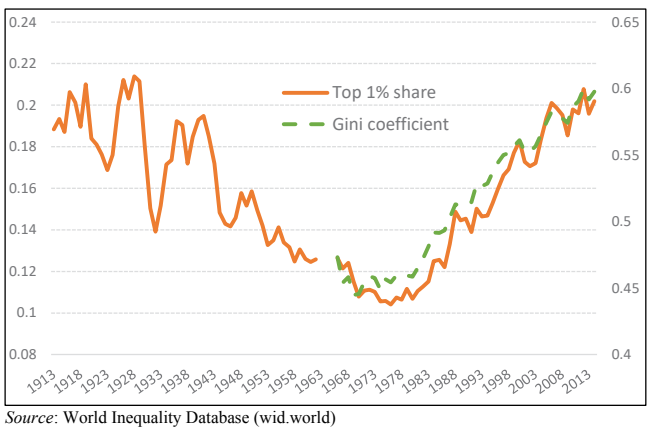
The paper begins with an overview of national-level trends in US inequality before moving on to a brief review of the literature. We then outline data sources and the modelling strategy. Next, we present results from our models before concluding with a discussion of our findings.

LITERATURE REVIEW

National-level trends

In the first half of the twentieth century, economic shocks brought on by two world wars and the Great Depression lowered top incomes, reducing US income inequality to relatively low, stable levels for much of the 1950s and 1960s, a period in time referred to as the Great Compression (Goldin & Katz, 2007) (see Figure 1). By the mid-1970s, the income distribution began to 'spread' as the poor grew poorer and the wealthier grew richer (Goldin & Katz, 2007).

Figure 1. Long-term evolution of income inequality in the US



Source: World Inequality Database (wid.world)

During the 1980s, inequality continued to rise in earnest; not only did top income shares grow far faster than the rest of the distribution, there was a concurrent expansion in lower tail income inequality (Autor & al., 2016). From 1979 to 2007, average annual incomes for the top 1% of households increased by 224% while the incomes of bottom 90% of households increased only 5% (Breau & Essletzbichler, 2013). Much of this growth occurred in the short period of time from the mid-1990s to the mid-2000s, and was directly followed by a period characterized by more volatile incomes (Breau & Essletzbichler, 2013).

The early years of twenty-first century saw inequality continue to rise, and top incomes reached levels that had not been since before the 1929 market crash (Piketty, 2014). Concurrently, lower- and middle-income individuals and households increased debt loads and reduced savings to maintain standards of living, practices that led to the inflation of the credit and mortgage bubble, which eventually burst in 2007 (Galbraith, 2012; Stiglitz, 2012). During the 2008-09 recession, incomes at the top remained stagnant, or declined slightly, while in some metropolitan areas, incomes at the bottom dropped as much as 25% (Berube and Holmes, 2016).

While the Great Recession momentarily slowed rising inequality, the top decile's income share soon recovered (Piketty, 2014). And although the recession nominally ended in 2009, recovery has been slow, as lingering conditions of high unemployment, reduced wealth, and smaller retirement incomes have placed disproportionate burdens on those excluded from the gains of growth (Breau & Essletzbichler, 2013). Despite relatively sluggish conditions, those in the top 1% have almost fully recovered with incomes increasing on average 17.4 percent from 2009 to 2013 (Sommeiller & al., 2016), Meanwhile, over the same period, the average income of the bottom ninety-nine percent grew a mere 0.7 percent (Sommeiller & al., 2016). And while incomes near the bottom dropped during the recession, they have yet to recover (Berube & Holmes, 2016). On the whole, U.S. inequality remains at historically high levels and this trend shows no immediate signs of abating.

Metropolitan studies

When zooming in at the sub-national level, increasing inequality tends to be most acute in large metropolitan areas. Urban centers concentrate people, industry, and capital. Dense clusters of capital and labour benefit those who cluster there, however, concentration begets congestion costs that drive up prices (e.g. land and housing) and wages (Polèse, 2009). High costs associated with city size means that highly skilled workers in larger metropolitan areas command higher prices; the wage premium that is associated with urban size therefore means that larger metropolitan areas are likely to experience greater inequality (Baum-Snow & Pavan, 2013; Behrens & Robert-Nicoud, 2014). Given such agglomeration dynamics, metropolitan areas are an ideal unit to examine individual and household economic outcomes within similar economic contexts.

Despite varied disciplinary perspectives and competing explanations, most research acknowledges that there are many determinants of inequality. Most of the existing studies of US inter-metropolitan inequality tend to be limited because they either (i) only provide cross-sectional glimpses of income inequality, (ii) are based on older data, or (iii) explore only one or two possible determinants at a time (Chakravorty, 1996; Silver & Bures, 1997; Donegan & Lowe, 2008; Bolton & Breau, 2012; Florida & Mellander, 2014).

Of the cross-sectional studies focused on the determinants of metropolitan inequality, several studies were conducted using data from the 1970s (Long & al., 1977; Garofalo & Fogarty, 1979), 1980s (Sakamoto, 1988), 1990s (Chakravorty, 1996; Levernier & al., 1998), 2000s (Volscho, 2005; Donegan & Lowe, 2008; Wallace, & al., 2012), and more recently the 2010s (Florida & Mellander, 2014; Essletzbichler, 2015; Berube & Holmes, 2016). While these cross-sectional studies help us understand the relationships between inequality and its determinants, they only provide a 'static' snapshot of what is occurring at one point in time.

Other research has taken a longer-term perspective on metropolitan income inequality. One body of work examines changes in income inequality from the post-war period to the latter part of the twentieth century (Kennedy & Nord, 1984; Wheeler, 2005). Another group of papers focuses on changes during the 1970 to 1990 period, when inequality grew quickly (Silver & Bures, 1997; Levernier, 1999; Wheeler, 2004). More recent work examines long-run changes in inequality through the 2000s (Glaeser & al., 2009; Lee & Rodríguez-Pose, 2013).

Much of the existing work on inequality has shown that the rise in national inequality is driven primarily by increasing metropolitan inequality. While there is some disagreement as to the exact cause of this phenomenon, cross-sectional and long-term studies alike have identified many factors that have driven the rise in inequality, which points to the need for a multi-dimensional framework when studying inequality. However, much of this research cannot speak to changes in inequality past 2000, and even fewer can address inequality post-recession.

Theoretical framework

Following the work of Chakravorty (1996) and Breau (2015), we develop an analytical framework based on elements identified as the key determinants of metropolitan income inequality. Drawn from the wider inequality literature, these determinants include the (i) economic, (ii) socio-demographic, (iii) institutional, and (iv) spatial characteristics of metropolitan areas.

Most research evaluates the impact of economic factors such as economic development, unemployment and industrial mix on inequality. The starting point for much inequality research is often considered to be Kuznets' (1955) seminal study that explored the relationship between inequality and *economic development* across industrialized countries. Kuznets found that as nations developed, inequality would initially rise until it reached an apex, and level off before declining (Kuznets, 1955). However, by the 1970s, scholars found that development above a certain threshold would lead to rising inequality (Bluestone & Harrison, 1988).

Many researchers link recent changes in the structure of labour markets (i.e. industrial mix) and available employment to the rise in income inequality. In part, this is tied to the deindustrialization hypothesis which attributes rising inequality to the transformation of the US economic base from manufacturing to the service sector. The bimodal wage structure of the service sector increases the spread of incomes, which coupled with the hollowing out of middle-income jobs, leads to increasing levels of inequality (Levernier & al., 1998; Wallace & al., 2012). At the same time, advances in technology led to skill-biased technological change that saw firms mechanize routine tasks to increase productivity, skewing labor demand toward more educated workers at the expense of blue-collar workers (Silver & Bures, 1997; Autor & Dorn, 2013).

Unemployment is also linked to higher income inequality as higher unemployment rates are generally indicative of weaker labour markets (Chakravorty, 1996). Such conditions depress wages, especially for low-skill occupations, and are characterized by more part-time/contractual employment and job loss (Wallace & al., 2012). Those in high-skill positions are unlikely to see a decline in income, possibly leading to an increase in top income shares (Chakravorty, 1996). Thus, research predicts that higher unemployment will lead to higher levels of inequality (Chakravorty, 1996; Lee & Rodríguez-Pose, 2013; Essletzbichler, 2015).

Socio-demographic factors also influence rising inequality. Population *age structure* can influence inequality in different ways. Some studies indicate that greater shares of young and the elderly will place pressure on the working population, increasing inequality (Levernier, 1999; Breau, 2015). Others argue that social security payments create an elderly middle class, compressing the income distribution (Levy & Michel, 1991). Growing *female labour force participation* is often linked to greater income inequality, as women workers earn less across occupations, are underrepresented in high paying positions, and are less likely to occupy management positions (MacLachlan & Sawada, 1997; Mihaila, 2016). Other studies find that more working women decreases inequality (Sakamoto, 1988; Kopczuk & al., 2010). Kopczuk & al. (2010) argue that income mobility has risen for women in recent decades, and the male-female earnings gap has decreased, meaning that greater female participation will lead to a decrease in inequality.

Changes in *education* and skills levels are commonly linked to income inequality (Chakravorty, 1996; Silver & Bures, 1997; Donegan & Lowe, 2008). The aforementioned economic transformation overwhelmingly favored skilled workers as improvements in technology increased demand for highly educated, highly skilled labour (Autor & Dorn, 2013). Computerization reduced demand for unskilled labour during a time where 'good' jobs with middle-class wages were eliminated or subject to pay cuts resulted in lower wages for the semi-skilled and low-skilled across the labour force (Autor & Dorn, 2013). Thus, higher levels of skill/education contribute to greater levels of inequality, as the spread of incomes increased across and within skill groups (Autor & Dorn, 2013).

Due to the history of systematic race-based discrimination in the United States, metropolitan *racial segregation* also drives inequality. Segregation concentrates poverty which creates mutually reinforcing spirals of decline, limiting access to labour and education markets (Smets & Salman, 2008). Segregation intensifies black-white income disparities, and leads to greater inequality (Smets & Salman, 2008; Sharma, 2017).

Immigration is often cited as a cause of inequality. Many studies argue that a rise in immigration creates a glut of low-skill workers, driving down wages, contributing to higher overall inequality (Chakravorty, 1996; Donegan & Lowe, 2008; Moller & al., 2009). However, highly skilled immigrants may also increase inequality by earning incomes that place them at the top-end of the distribution, and depreciating the earnings of competing workers (Borjas, 2005).

Institutional factors traditionally counterbalance rising inequality. Greater *unionization* generates wage compression that produces relatively high and egalitarian wages among workers in sectors with active unions as well as fostering workplace norms and standards (DiNardo & al., 1996; Volscho, 2005). Thus, places with the strongest unions tend to have the lowest levels of inequality (Brady, 2003). However, with declining US unionization many argue unions are no longer able to exert equalizing pressure on the income distribution (Donegan & Lowe, 2008; Wallace & al., 2012). *Minimum wage* thresholds are thought to lower inequality by compressing the wage distribution (Volscho, 2005; Autor & al., 2016); however, others point out that since minimum wages have not kept up with inflation they could increase dispersion at the bottom of the income distribution (Dinardo & al., 1996).

METHODOLOGY

Data Sources and Development

The analysis carried out in this paper relies on data from multiple sources. All dependent and several independent variables were compiled using the Integrated Public Use Microdata Series (IPUMS) (Ruggles & al., 2017). This dataset uses 5% samples of the 1980, 1990, and 2000 US Census, and the 2010 1% American Community Sample. Segregation data was obtained from the American Communities Project. Institutional data on unionization was developed using the US Current Population Survey (Hirsch & Macpherson, 2017) and minimum wage data comes from the US Department of Labor (DOL, 2017). These variables are available for a sample of 226 metropolitan areas that were consistently documented across Census and ACS.

To study the patterns of inequality, we examine two income concepts: (1) wages and salaries and (2) total income which includes capital gains and rent along with pre-tax wage and salary income. Inequality is measured using three different indicators: the Gini coefficient, the Theil index, and the top 1 percent share of income. Since each of these indicators is sensitive to income transfers in different parts of the distribution, a three-pronged approach provides more robustness to the analysis.

One limitation to this data lies in topcoding, a censorship practice adopted by the US Census Bureau in order to "maximize confidentiality and minimize exposure risk" (Jenkins & al., 2009). Published income values for individuals are right-truncated, which can bias the analysis by cutting off the upper tail of the income distribution, thus artificially lowering inequality measurements (Feng & al., 2006, Jenkins & al., 2009). Not only does this distort measurements of income distributions, estimation is further biased because topcodes have not been adjusted consistently over the years which leads to variations in the definition of high income cut-offs from year to year (Jenkins & al., 2009). To address variability and uncertainty, this research uses a multiple imputation approach that draws upon Generalized Beta of the Second Kind distributions (as developed in Jenkins & al., 2009) to measure inequality trends in partially synthetic datasets. This technique produces estimates that are significantly lower than estimates reported by the Census Bureau using uncensored data, but they remain reflective of income trends over the same period (Feng & al., 2006).

Summary statistics

Table 1 reports the changes in different measures of metropolitan inequality across 226 metropolitan areas. Summary statistics show that while both total income and wage inequality increased, total income inequality grew at a much faster pace throughout the 1980s and 1990s. Additionally, growth in upper-tail inequality measures was more substantial than growth in average Gini values, indicating that growth in inequality is in part due to capital gains and rents.

During the volatile 2000-2010 period encompassing the Great Recession, trends in total income inequality and wage inequality diverged. After significant increases, total income inequality stagnated (i.e., Gini) or began to decline (i.e., Theil index, top shares). However, wage inequality (i.e., Gini and Theil values) continued to grow, with top wage earners experiencing a slight decline in wage shares over the 2000-2010 period. The decrease in total income inequality may indicate that many of the losses in the recession are linked to a decrease of capital gains in the upper income strata even though top incomes continued to rise. Additionally, larger MSAs tend to experience both higher levels of inequality, and faster growth in inequality.

This latter observation is better seen in Figure 2 which provides a snapshot of inequality across MSAs in 2010. Many of the most populous metropolitan (e.g., Los Angeles, Miami, Boston, Houston, San Francisco) areas have Gini coefficients of over .53, and other large MSAs (e.g., New York, Chicago, Dallas) are not far behind. Many of these large agglomerations are regional and global economic hubs (i.e., NY, LA, Chicago, New Orleans), and many have prominent roles in particularly productive sectors (e.g., Los Angeles and entertainment,

Table 1. Selected summary statistics on income inequality across MSAs

	Income Inequality				Percentage change		
	1980	1990	2000	2010	1980-1990	1990-2000	2000-2010
Mean Total income Gini value	0.452	0.487	0.513	0.515	8%	5%	0%
Mean Total income Theil's T value	0.356	0.433	0.536	0.505	22%	24%	-6%
Mean Total income Top 1% share	5.9	7.9	11.1	9.7	34%	41%	-13%
Mean W&S income Gini value	0.447	0.465	0.478	0.489	4%	3%	2%
Mean W&S income Theil's T value	0.348	0.396	0.445	0.459	14%	12%	3%
Mean W&S income Top 1% share	5.9	7.4	9.2	8.8	25%	24%	-4%
Selected metrics by MSA size							
Mean Total Inc. Gini value							
>2 million	0.449	0.489	0.515	0.518	9%	5%	1%
2mil-750k	0.449	0.482	0.509	0.51	7%	6%	0%
750k-400k	0.449	0.479	0.499	0.502	7%	4%	1%
400k-250k	0.456	0.485	0.495	0.502	6%	2%	1%
<250k	0.463	0.481	0.499	0.498	4%	4%	0%
Mean Total Inc. Top 1% share							
>2 million	5.8	8.2	11.5	9.8	41%	40%	-15%
2mil-750k	5.9	7.9	11.2	9.6	34%	42%	-14%
750k-400k	5.8	7.5	10.3	9.2	29%	37%	-11%
400k-250k	5.7	7.5	9.8	8.8	32%	31%	-10%
<250k	6.1	7.3	9.9	8.7	20%	36%	-12%
Mean W&S Top 1% share							
>2 million	5.7	7.7	9.7	8.9	35%	26%	-8%
2mil-750k	5.9	7.4	9.2	8.9	25%	24%	-3%
750k-400k	5.8	6.9	8.3	8.3	19%	20%	0%
400k-250k	5.6	6.9	8.1	7.9	23%	17%	-2%
<250k	5.8	6.6	7.9	7.9	14%	20%	0%
Obs.	**226**	**226**	**226**	**226**			

Boston and health care). Dense concentrations of labour and capital around a few key sectors reinforce clustered development patterns, driving up costs and wages, leading to greater levels of inequality in larger MSAs.

Modelling Strategy

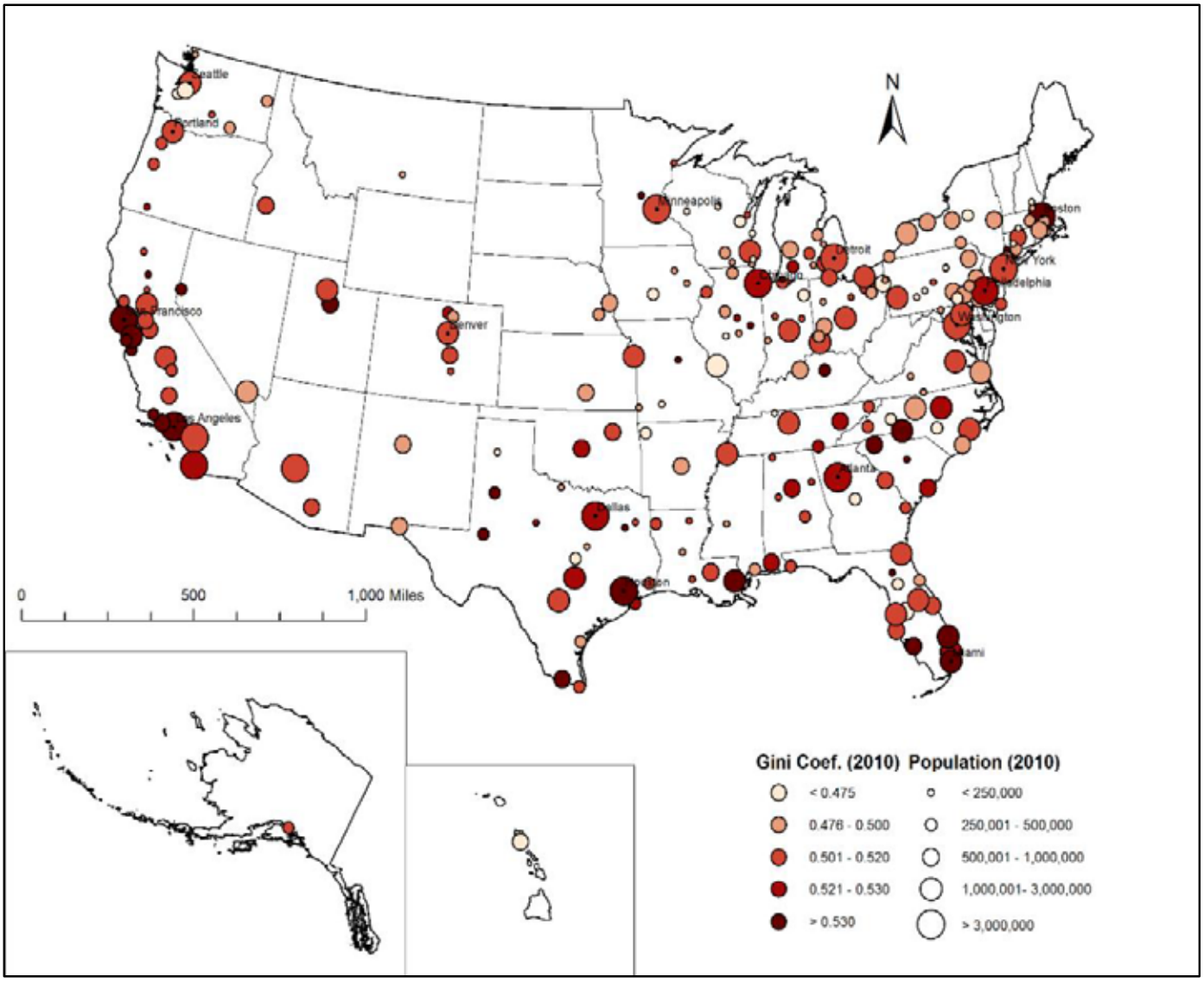
To interrogate the link between inequality and proposed causal factors, we estimate two sets of models. Pooled OLS models are used to examine long-term trends in inequality, whereas fixed effects models are geared toward examining shorter-term changes in the drivers of inequality. Following the work of Chakravorty (1996) and Bolton & Breau (2012), the pooled OLS model is specified as:

$$INEQ_{it} = \alpha + ECON_{it}\beta + SOCDEMO_{it}\theta + INST_{it}\gamma + IND_{it}\mu + 1990\delta_0 + 2000\delta_1 + 2010\delta_2 + \varepsilon_{it}, \quad (1)$$

where the dependent variable is the inequlity metric for metropolitan area i in year t (with t = 1980,1990, 2000, and 2010). As per the theoretical framework discussed earlier, vectors representing the urban economic, socio-demographic, and institutional characteristics of MSAs are included on the right-hand side of the model. ECONit is a vector of economic variables controlling for demand-side factors (i.e. economic development and unemployment), and SOCDEMOit represents socio-demographic traits such as age structure, education levels, race, gender, and immigration. INSTit is a vector of institutional factors (i.e., unionization and minimum wages), and INDit is a vector of industrial control variables. In Eq. 1, using 1980 as the base year, dummy indicators for the years 1990, 2000 and 2010 are included to control for unobserved longitudinal 'macro' shocks (i.e., national-level events) that may affect all cities included in the analysis. Lastly, α represents the intercept while εit represents the usual error term.

Economic development is proxied by an MSA's median total income. We expect to see higher development levels increase inequality, especially in large MSAs. *Unemployment* represents the percentage of unemployed people in the metropolitan labour force. The age structure is captured by the *dependency ratio* which measures the ratio of dependents (people over 65 and younger than 16) to those of working age. In-line with previous studies, we expect that increases in the proportion of 'dependents' in relation to labour will result in higher inequality. Female labour force participation is represented by the percentage of women in the work force. We expect a greater proportion of female labour will decrease overall levels of inequality. *Education* is based on the ratio of people without a high school

Figure 2. Levels of inequality across US metropolitan areas, 2010



diploma plus those with advanced degrees to the rest of the population, which represents workforce skill differentials (i.e., educational inequality). We expect that greater skill dispersion will lead to greater inequality. The *immigrant population* variable is measured by taking the percentage of the foreign-born population, and we predict immigration to be associated with higher levels of inequality. The *segregation* variable is measured by the Duncan index of dissimilarity and drawn from the American Communities Project's database (Logan, 2011). This study expects higher levels of segregation to be associated with greater inequality in cities.

The institutional variables are available at the state level only and are thus used here as contextual variables. The *unionization* variable represents the percentage of the unionized workforce. Minimum wage indicates the minimum wage in each state for each year (DOL, 2017). Despite weak *minimum wage* levels in the US, this study expects higher minimum wage laws to dampen income inequality.

Where the pooled OLS model specified in Eq. (1) looks at longer-term trends, fixed effects models are employed to explore how short-term changes (i.e., decade to decade) across metropolitan areas affect inequality. A number of recent studies use fixed effects models to investigate changes in inequality (Lee, 2011; Lee & Rodríguez-Pose, 2013; Breau & al., 2014; Marchand & al., 2017). Fixed effects models assume that unobserved effects within an entity impacts the dependent or independent variables, and control for these time-invariant effects to examine how the independent variables impact the dependent variable (Wooldridge, 2013). Fixed effects models assume that time-invariant variables are unique, and not correlated with other individual characteristics (Wooldridge, 2013; Lee, 2011). Lee (2011) argues that this is ideal in cases where there are likely to be social factors which will change the data but are unlikely to undergo significant changes during the time period in question. Following the work of Lee & Rodríguez-Pose (2013), Breau & al. (2014), and Marchand & al. (2017), the fixed effects model is specified as:

$$INEQ_{it} = \alpha + ECON_{it}\beta + SOCDEMO_{it}\theta + INST_{it}\gamma + IND_{it}\mu + vi + \delta_t + \varepsilon_{it}, \quad (2)$$

where the dependent variable is again the measure of inequality for metropolitan area i in year t. On the other side of the equation, as with Eq. (1), a series of vectors are included in the model: ECONit for economic factors, SOCDEMOit for socio-demographic indicators, INSTit for institutional variables, and INDit represents industrial sector control variables. The error term is composed of vi, a time-invariant individual fixed effect, δt, a time fixed effect (to reflect trends

Table 2. Fully-specified population-weighted pooled OLS regression results, 1980-2010

	(A) Gini		(B) Theil's T		(C) Top 1% Share	
	Total	W&S	Total	W&S	Total	W&S
Development	.001 (.804)	0.001 (0.246)	0.001 (.401)	0.001 (0.706)	0.001 (.518)	0.001 (0.160)
Unemployment	.247 (.000)***	0.238 (0.000)***	.409 (.012)**	0.423 (0.004)***	-0.022 (.579)	0.011 (0.759)
Dep. Ratio	.012 (.392)	0.008 (0.542)	.048 (.208)	0.025 (0.453)	0.009 (.316)	0.003 (0.522)
FPR	-0.099 (.017)**	-0.067 (0.124)	-.186 (.098)*	-0.067 (0.507)	-0.002 (.935)	0.017 (0.522)
Education	0.010 (.000)***	.012 (0.000)***	.017 (.000)***	0.017 (0.000)***	0.001 (.000)	0.001 (0.228)
Segregation	0.001 (.000)***	.001 (0.000)***	.001 (.000)***	0.001 (0.000)***	0.001 (.000)***	0.001 (0.000)***
Immigration	0.041 (.000)***	0.009 (0.337)	.158 (.000)***	0.048 (0.000)***	0.053 (.000)***	0.038 (0.000)***
Min. Wage	0.001 (.796)	0.001 (0.362)	-.001 (.917)	0.001 (0.764)	-0.001 (.743)	-0.001 (0.624)
Union	-0.001 (.000)***	-0.001 (0.000)***	-.002 (.000)***	-0.002 (0.000)***	-0.001 (.000)***	-0.001 (0.000)***
Year Dummies						
1990	.032 (.000)***	0.017 (0.00)***	.061 (.000)***	0.036 (0.000)***	0.016 (.000)***	0.011 (0.000)***
2000	.054 (.000)***	0.027 (0.00)***	.149 (.000)***	0.072 (0.00)***	.043 (.000)***	0.025 (0.000)***
2010	.061 (.000)***	0.049 (0.000)***	.121 (.000)***	0.090 (0.00)***	.028 (.000)***	0.019 (0.000)***
Constant	.397 (.000)***	0.388 (0.000)***	.158 (.118)	0.195 (0.031)**	.026 (.348)	0.028 (0.231)
Ind. Controls	Yes	Yes		Yes		Yes
N	**904**	**904**	**904**	**904**	**904**	**904**
R2	**0.729**	**0.553**	**0.725**	**0.581**	**0.775**	**0.669**

common across metropolitan areas) and εit as the usual idiosyncratic error. This time-fixed effect indicator will identify trends common across metropolitan areas.

Additionally, *geographic context* is considered by taking population size into account. The analyses are weighted by population size to ensure results account for variations among metropolitan populations.

CAUSES OF METROPOLITAN INEQUALITY

Long-term trends: Pooled OLS regression analysis

Table 2 presents empirical results for the pooled OLS analyses. The table is divided into three panels, with each panel presenting the fully specified Eq. (1) results for three measures of inequality: the Gini coefficient, Theil's T, and the top one percent share of income using both income concepts defined earlier.

Results show that unemployment is positively associated with inequality in the Gini and Theil models. Higher levels of unemployment are linked to higher total and wage income inequality, corroborating research that finds inequality rises during periods of high unemployment (Chakravorty, 1996; Lee & Rodríguez-Pose, 2013). Weak labour markets typically depress wages, mostly for low-skill occupations, leading to higher levels of inequality (Chakravorty, 1996).

Several socio-demographic factors have statistically significant long-term impacts on inequality. In the total income Gini and Theil models, female labour force participation has a negative relationship with inequality. While this contradicts research that argues that women's participation in the labour force will increase inequality via the male-female wage gap (MacLachlan & Sawada, 1997; Moller & al., 2009), it corroborates studies that find a greater percentage of working women decreases inequality (Sakamoto, 1988; Kopczuk & al., 2010). While we are uncertain as to why this is the case, Kopczuk & al. (2010) suggest the negative coefficient may be indicative of an increase in women's earnings relative to men, effectively compressing the income distribution and decreasing inequality.

Other results are in-line with the expected relationships. Educational dispersion is positively related to both total and wage income inequality in the Gini and Theil models. This supports the literature arguing that educational (and skill) dispersion drives income inequality, as the demand for skill increases incomes of high-skill occupations, while depressing wages for low-skill workers. The increased spread of incomes (linked to skill) drives up inequality (Autor & Dorn, 2013). Segregation is positively linked to total income and wage inequality in every model, providing support for claims that deeper segregation increases inequality. Many studies link race to inequality, finding that racial isolation in labour and housing markets will exacerbate income differences between racial groups, therefore increasing inequality (Chakravorty, 1996; Wallace & al., 2012; Sharma, 2017). Immigration populations are positively linked to inequality in total income models and upper-tail inequality wage models, supporting studies that link a larger immigrant population to higher inequality (Wheeler, 2004; Borjas, 2005; Donegan & Lowe, 2008; Moller & al., 2009). Unionization is also negatively related to inequality, in-line with findings that argue institutional controls play an important role in compressing the income distribution and reducing inequality (DiNardo & al., 1996; Volscho, 2005).

In summary, over the long-run, we find a number of factors that influence rising levels of inequality. On the demand-side, high levels of unemployment are linked to conditions of high income and wage inequalities. On the supply-side, factors relating to educational dispersion, segregation, and immigration all positively influence total income and wage inequalities, while female labour force participation only impacts total income inequality. Additionally, places with institutional protection in the form of unions experience lower levels of inequality.

Table 3. Fully-specified population-weighted fixed effects regression results, 1980-2010

	(A) Gini		(B) Theil's T		(C) Top 1% Share	
	Total	W&S	Total	W&S	Total	W&S
Development	0.001 (.00)***	0.001 (0.001)***	0.001 (0.001)***	0.001 (0.001)***	0.001 (0.001)**	0.001 (0.001)
Unemployment	0.291 (.066)***	0.286 (0.061)***	0.463 (0.179)**	0.488 (0.144)***	-0.005 (0.045)	0.005 (0.04)
Dep. Ratio	0.013 (.022)	0.029 (0.02)**	0.014 (0.059)	0.081 (0.048)*	0.006 (0.015)	0.021 (0.013)
FPR	-0.135 (.055)**	-0.085 (0.051)*	-0.571 (0.149)***	-0.335 (0.121)***	-0.115 (0.038)***	-0.076 (0.034)**
Education	0.001 (.001)	0.002 (0.001)*	0.005 (0.003)	0.007 (0.003)***	0.002 (0.001)***	0.003 (0.001)***
Segregation	0.001 (.001)	0.001 (0.001)	0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)**	-0.001 (0.001)**
Immigration	0.109 (.028)***	0.025 (0.026)	0.209 (0.076)***	0.041 (0.062)	0.031 (0.019)	0.006 (0.017)
Min. Wage	-0.001 (.001)	-0.001 (0.001)	-0.001 (0.003)	-0.003 (0.002)	0.001 (0.001)	-0.001 (0.001)
Union	0.001 (.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Year Dummies						
1990	0.025 (.004)***	0.008 (0.003)**	0.055 (0.01)***	0.025 (0.008)***	0.017 (0.003)***	0.012 (0.002)***
2000	0.041 (.006)***	0.015 (0.005)***	0.128 (0.016)***	0.057 (0.013)***	0.042 (0.004)***	0.027 (0.004)***
2010	0.033 (.009)***	0.029 (0.009)***	0.096 (0.025)***	0.088 (0.020)***	0.034 (0.006)***	0.033 (0.006)***
Constant	0.458 (.036)***	0.446 (0.033)***	0.493 (0.097)***	0.403 (0.078)***	0.105 (0.024)***	0.081 (0.022)***
Ind. Controls	Yes	Yes	Yes	Yes	Yes	Yes
N (MSAs)	**226**	**226**	**226**	**226**	**226**	**226**
N	**904**	**904**	**904**	**904**	**904**	**904**
R2	**0.754**	**0.606**	**0.758**	**0.629**	**0.811**	**0.689**

Short- and medium-term effects: Fixed effects analysis

Table 3 presents empirical results for the fixed effects analyses. As above, the table is divided into three panels, with each panel presenting the fully specified Eq. (2) results for three measures of inequality: the Gini coefficient, Theil's T, and the top one percent share of income. Fixed effects models estimate how changes within individual entities (i.e., MSAs) across time affect outcomes (i.e., inequality). In controlling for time-invariant characteristics, we assess the effect that fluctuating predictors have on both total income and wage inequality (Wooldridge, 2013).

Once again, greater educational dispersion is linked to higher inequality. However, this relationship is only significant in the wages and salary model, suggesting that while the wage premium is driven by education levels, returns from other sources of income may be tied to factors other than education and skills. Higher unemployment is also associated with both higher total income and wage inequality, reinforcing previous results. Short-term increases in levels of female labour are linked to lower inequality. Again, this may reflect a decrease in the gender wage gap, which places downward pressure on the distribution and results in lower inequality (Kopczuk & al. 2010). The results also suggest that larger metropolitan immigrant populations drive total income and wage inequality.

Compared to Table 2, some of our fixed effects estimates show statistically significant relationships that did not appear in the pooled OLS models. Higher levels of economic development are positively linked to both total income and wage inequality, which is in-line with findings that associate increasing development levels to growing inequality. Contrary to our previous results, a greater ratio of dependents to labourers is linked to higher wage inequality. This is consistent with findings that argue more dependents strain the existing labour force. On the other hand, the fixed effects models show that unionization no longer has a statistically significant effect on income inequality.

More puzzling here are the divergent relationships that emerge in the segregation estimates. While the positive sign for the inequality-segregation relationship that appears in the total income and wage Gini inequality models (as well as the total income Theil's T) reflect our previous results, the coefficient estimates are not statistically significant. That said, there is evidence that greater segregation is linked to a lower share of total income for the top one percent. One explanation for the positive (albeit not significant) link to wage inequality, and the significant and negative link with top incomes, could be that the largest MSAs have experienced more dramatic decreases in segregation over time. Places with more significant increases in levels of segregation may therefore be small- to mid-size MSAs, where the highest earners have a smaller relative share of top incomes, and have less income sourced from capital gains and rents than in larger MSAs with more activity in FIRE sectors.

Overall, looking at how changes in explanatory factors have influenced metropolitan inequality, while controlling for unobserved heterogeneity, we find several parallels with many of the long-term results reported in the previous section. Structural changes in demand-side conditions, workforce composition, and institutional protections continue to play a strong role in predicting rising metropolitan inequality.

CONCLUSION

US metropolitan income inequality has changed significantly over the past four decades. First, we found that inequality has risen substantially since 1980. While total income inequality increased faster than wage inequality, they both grew throughout the 1980-2000 period, increasing fastest from 1990 to 2000. From 2000 to 2010, inequality trends diverged. Total income Gini values were stagnant, while wage income Gini and Theil values continued to rise, albeit at a slower rate. Metrics measuring upper-tail total income inequality and top wage shares showed decreasing levels of inequality, indica-

ting that the recession especially impacted top incomes and wages. These effects were most striking in the largest MSAs.

Our model estimates provide some insights into the drivers of inequality. High levels of educational dispersion are a consistently important determinant of inequality. In both pooled OLS and fixed effects models, education had a greater impact on wage inequality; however, short-term models indicate greater skill dispersion has a larger effect on upper-tail income inequality. The extent of segregation and the percentage of the immigrant population are also consistently linked to greater inequality. Development levels are generally positively related to inequality, providing support for the 'U-turn' hypothesis. Both short- and long-term models indicate that more female labour tends to decrease inequality, especially in terms of total income inequality. Results for unemployment support previous research findings of a positive association between unemployment and inequality.

Other factors have less constant effects. Short-term estimates indicated more dependents will increase inequality; however, this factor is not significant in long-term models. Long-term models also show that greater unionization compresses the income distribution and results in lower levels of inequality. However, once time invariant factors are taken into account, this relationship is no longer significant.

Of course, there are limitations to this study. While the quality of the data is high, it is unable to completely capture the extent of inequality as a result of censored income characteristics. Top-coding ultimately reduces inequality estimates, meaning that our analysis underestimates the level of inequality. We are also only able to include contextual (state-level) institutional factors, due to the limited availability of metropolitan-level data. Decade-long panels meant that we are unable to look at shorter-term evolutions in inequality, nor did we have variables able to directly account for the SBTC argument which is also seen as an important driver of inequality in the literature. Future research could perhaps investigate the effect of SBTC by using a proxy measure such as the variation in patent counts across metropolitan areas (e.g., Breau & al., 2014).

Nevertheless, the results presented in this chapter generally reinforce theories common in the literature (i.e., the Great U-turn, and supply-side theories focusing on workforce demographics), and reinforce assertions that changes in the distribution of income are not driven by one single factor. Part of this rise in inequality is driven by increasing returns to top incomes, seemingly due to increased returns to skills. However, other measurements indicate that higher levels of inequality are also driven by changes in the middle- and lower- parts of the income distribution. A large part of inequality has been determined by socio-demographic changes, and an economy that disproportionately benefits the most-highly skilled labourers.

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