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Financial Crisis and the Increase of Income Equality across Cities

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Abstract

This paper investigates why the level of income inequality differs across U.S. cities. We also explore why some cities experienced faster increases in the level of inequality than others. Using the Decennial Census and the American Community Survey (ACS) from 1980 to 2011, we explore whether the disparities in the level and the changes in the level of inequality can be explained by MSA characteristics, including labor market conditions, skill distribution, residential mobility, racial concentration, industrial composition and unionization. We also examine how state level policies such as unemployment insurance benefits and minimum wage level is associated with income inequality.

Our findings shows that negative labor market conditions, concentration of skilled workers and racial segregation are positively associated with the level of income inequality. The level of inequality in these cities also tends to rise grow at a faster pace. While the minimum wage do not seem to have any association with income inequality, we find some evidence that the unemployment insurance benefit and percent of union members lower the increase in the income inequality.

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I. Introduction

This paper investigates why there are differences in the levels and changes in the levels of income inequality across Metropolitan Statistical Areas (MSAs) from 1980 to 2011. Growing levels of income inequality in the U.S. have gained great attention from the policy makers, media and scholars. The concerns have increased since 2007, as the financial crisis produced greater income disparities between the rich and the poor. Specifically, following the crisis, the real income level of the bottom 10th percentile experienced a greater percentage drop compared to the top 10th percentile. Also, the income level of the bottom 10th percentile has shown slower recovery since 2007[3].

So far, studies examining the impact of the financial crisis on inequality have not investigated the heterogeneity in changes in the level of inequality across MSAs. In fact, while the average level of inequality went up following the crisis, almost 40 percent of the MSAs have experienced a decrease in the level of inequality during this time period. Moreover, there exists a high level of heterogeneity in the levels of income inequality across MSAs. For example, in 2011, the income ratio of the top 10th percentile to bottom 10th percentile of MSAs ranged from Sheboygan, Wisconsin's low of 5.92 to Athens, Georgia's high of 30.25. The discrepancy in the level and the changes in the level of income inequality across MSAs leads us to wonder whether there are measurable characteristics that explain these variations. And if so, can MSAs with high income inequality pursue policies that will allow them to mitigate inequality?

Using data from the Decennial Census and the American Community Survey (ACS), this paper explores whether the disparities in the level of inequality across MSAS can be explained by MSA characteristics, including labor market conditions, skill distribution, residential mobility, racial concentration and industrial composition and unionization. We also examine whether state level policies such as unemployment insurance benefits and minimum wage level is associated with income inequality.

While many studies have looked at changes in inequality at the national level (e.g. Acemoglu, 2002; Autor et al., 2008; Attanasio, 2013), not many have examined the changes in the inequality at a city level. The main advantage of looking at income inequality at a city level is that we can execute a cross sectional or a panel analysis to determine factors that explain differences in the level and changes of income inequality. And unlike cross-country comparisons, within one country cross-city comparisons allow us to better control for the political or the institutional environment, and obtain consistently measured dependent and explanatory variables[4].

The disadvantage of using MSAs as the unit of analysis is that people can easily move across

[3] Our data analysis shows that from 2008 to 2009 the real income of the bottom 10th percentile dropped by 7.00 percent while that of the top 10th percentile dropped by 4.70 percent. During the 2010-2011 period, the real income of the bottom further dropped by 3.89 percent, while the percent drop was only 0.30 percent for the top 10th percentile.

[4] For example, it is difficult to acquire comparable inequality index, as countries report incomes differently. One major difference is that some countries report after tax income while others report pre-tax income.

cities. This makes it challenging to capture variables that affect the income inequality, as many people come and go. Another limitation of using MSAs as a unit of analysis is related to the fact that these areas do not exactly correspond to political units, thus making it difficult to link precisely state policies with MSA outcomes.[5]

Our studies make several novel contributions to the existing studies which looked at the city level inequality (Watson 2009; Glaeser et al., 2009; Baum-Snow, 2013). First not only do we create a panel data to verify factors that explain the changes in the level of inequality, we use a difference in differences framework to identify whether the relationship between changes in the level of inequality and skill and racial composition changes in different time periods. We also decompose the inequality data and examine whether changes in inequality are due to the changes in the income of the rich or that of the poor. Furthermore, our study has a rich set of explanatory variables. Thus, we are able to expand our understandings of how and why the inequality level differs in cities and also provide better explanation for why the changes in income inequality differ across these areas.

In sum, we find that the level of income inequality is greater is areas with higher unemployment and lower labor force participation rates, greater proportions of skilled laborers, higher degrees of racial segregation and greater amounts of industrial specialization. Also, the level of inequality changes more across time in MSAs where labor market conditions worsens and where unionization is less prevalent. Meanwhile, skill distribution and racial concentration have different associations with changes in income inequality in different time periods. Among the policy variables, unemployment insurance benefit programs show some level of effectiveness in reducing income inequality.

The remainder of this paper is organized as follows: Section II provides the background of this paper by reviewing existing literature that discusses the rise in the income inequality. In section III, we describe the data and methodology. Section IV presents the empirical results and Section V concludes.

II. Background

Contrary to the prediction of the Kuznets curve (1955), the U.S. economy has recently not seen average income growth produce lower income inequality. In fact, it is well documented that the income inequality has consistently increased since 1980. Figure I shows the changes in the ratio between the top and the bottom 10th percentile of the income distribution from 1980 to 2011. The graph shows that U.S. income inequality increased during the 1980-2000 period, slightly decreased from 2000-2006, and then rose again from 2007-2011. Figure II shows that the absolute changes in the level of income for the top 10th percentile have been volatile, but for the bottom 10th percentile have been flat.

So far, studies which examined the rise in inequality attribute this phenomenon to a

[5] We chose to use MSAs over states, as MSAs are closer approximations to individual job markets than states. States consist of multiple job markets, which may obscure the relationship between the level of income inequality and explanatory variables such as unemployment.

combination of three of the following forces[6]. First, the technology revolution (such as the computerization of the labor force) has rapidly increased the demand for high skilled workers and increased their returns to skill. Second, the erosion of the labor market institutions that protected the low income workers. Two commonly mentioned examples are a falling real minimum wage and a decline in unionization. The proponents of this argument claims that the fall in the real value of minimum wage and the decline in unionization lowered the real wage of the less skilled workers. Third, the impact of international trade and the concomitant increase of returns to capital have disproportionally benefited the rich relative to the poor.

In this study we focus on the first two forces. We do not look at the impact of globalization on inequality, but reserve it as a potential area of future study. But beyond investigating the impact of skills and institutions, we examine whether racial composition and segregation, and industrial diversity, also provide some explanation for the differences in the level and the changes in income inequality across cities.

III. Data & Methods

Dependent Variables: Level and Changes of Income Distribution

In our analysis we use three dependent variables: 1) the difference in the log of income for the top and the bottom 10th percentiles of the income distribution; 2) the log real income of the top 10th percentile; and 3) the log real income of the bottom 10th percentile. We calculate this measure for each MSA using the data from the decennial census and the American Community Survey for the following years: 1980, 1990, 2000, 2005-2011[7]. We use before tax income data, as we aim to identify how the income is distributed before the government intervention and what factors explain the income distribution.

The difference in the log income of the top and the bottom 10th percentiles is a commonly used proxy of income inequality along with the Gini coefficients[8]. The benefit of using this proxy over the Gini coefficient is that we can decompose the index to examine whether the changes in the level of inequality is due to the changes in the income of households in the top or the bottom of the income distribution. Figure III illustrates the shares of MSAs which experienced an increase in the level of inequality over the 1980-2010 period. From 1980 to 1990, the level of inequality increased in 85.71 percent of MSAs. The percentage of MSAs that experienced an increase in inequality dropped to 68.55 percent during 1990-2000, but went back up to 80.81 percent during 2000-2010.

While the percent of MSAs that showed an increase in inequality is similar between the 1980-1990 period and 2000-2010, we can observed clear differences across the two periods, if we decompose the changes in inequality by changes in the income of the top and the

[6] For a detailed review, refer to Acemoglu (2002) and Autor et al. (2008)

[7] We use the census for 1980, 1990, 2000 and the ACS for 2005-2011.

[8] We also calculated the Gini coefficients for the same periods of time and found that the correlation between the Gini index and the difference in the log income for the top and the bottom 10th percentile is 77.01 percent.

bottom 10th income percentiles. Among MSAs that experienced an increase in inequality during 1980-1990, 53.76 percent experienced increases in both the income of the top and the bottom deciles. However, for the latter period, only 8.25 percent of MSAs experienced an increase in the real income of both income percentiles while 70.83 percent of MSAs experienced a decrease in the real income for both the bottom and the top. This shows that there may be different reasons for the changes in income inequality in different time periods. By looking at the changes in the top and the bottom deciles, we could better understand the reason for the inequality changes.

Using the levels of these three measures and the changes of these measures of income distribution as our dependent variables, we execute a regression analysis with various MSA and State level variables.

Explanatory Variables: MSA Level

Labor Market Conditions

The first two explanatory variables are the two proxies of labor market conditions: 1) MSA level labor participation rate and 2) MSA level unemployment rate. Rather than using the data from the Bureau of Labor Statistics (BLS), we calculate these two measures using the Decennial Census and the ACS. We do this because we think our estimated values of unemployment[9] and labor participation rate better match our proxies of income distribution as they are all calculated from the same data sets.

We hypothesize that areas with lower labor participation rates and higher unemployment rates are more unequal. We further hypothesize that the level of inequality will rise more in areas where the unemployment rate increases and the labor participation rate decreases. This is based on the theory of Williamson (1981), who suggests that the high skilled workers are more likely to be hired and less likely to be laid off as they possesses skills that may be relatively more difficult to replace. Hence low-income workers, who are typically less skilled, will see their incomes drop as they become unemployed, whereas high-income workers will continue to remain employed. High skilled workers incomes might not rise under such circumstances, but they will not fall less. This will exacerbate inequality.

Skill Distribution & Mobility

Skill distribution is also measured by two proxies: 1) the share of those over 25 years old that received a Bachelor degree and 2) the share of those over 25 that dropped out of high school. These variables are also calculated using the ACS and the Census data. According to Glaeser et al. (2009), differences in the skill distribution can explain 30 percent of the variance in income inequality across MSAs.,Glaeser and co-authors do note, however, that it is still unclear why places with a greater proportion of BA degree holders are more unequal. For example, this could due to the positive spillover effect of human capital which

[9] Note that the correlation between the unemployment rate from the BLS and our estimated unemployment rate is 80.00 percent.

disproportionately influences higher income households more than the poor. It could also be due to a faster improvement in technology that benefits the high skilled workers in areas with greater share of highly educated population. Alternately, it might reflect the fact that the skilled people migrate towards area with greater returns to skill. While it is difficult to disentangle the cause of these phenomena, we include MSA's net mobility rate of both BA holders and high school drop-outs in our regression to partially control for the migration effect[10].

Racial Composition & Segregation

The next explanatory variables are related to racial composition and segregation in MSAs. The racial composition is measured by calculating the share of blacks, Hispanics and Asians, using the Census and the ACS data. For racial segregation, we used the dissimilarity index, which is one of the most commonly used indices. This index shows the relative proportion of minorities who would have to exchange tracts with whites to achieve an even residential distribution and is measured as

$$\text{Dissimilarity Index (Black)} = \frac{1}{2}\sum_{i=1}^{n}\left|\frac{Black_i}{Black} - \frac{White_i}{White}\right| \qquad (1)$$

Where $Black_i$ is the number of blacks in census tract i, within the MSA and $Black$ is the total number of blacks in the MSA. Same holds for $White_i$ and $hite$. A higher value of the index indicates greater segregation between the two groups. We also calculate the dissimilarity indices for Hispanics and Asians.

Using these measures we test for a hypothesis that the income level of the bottom 10th percentile is lower in areas with greater share of minority population (especially blacks) and also in areas with greater racial segregation. This hypothesis is based on several theories, including Kain's (1968), which suggests that minorities are worse off in areas with greater segregation, due to greater spatial mismatch in segregated cities between the location of jobs and the places where minorities live. Also, in highly segregated areas minorities may receive less benefit from the peer effects (Coleman, 1966) or social interaction (Borjas, 1995). In accordance with these theories, Cutler and Glaeser (1997) finds that blacks in more segregated areas are likely to have lower incomes of being unemployed when compared to blacks in less segregated areas.

Industrial Diversity

Another MSA level control variable we include in our analysis is the extent of industrial diversity. Existing studies (Neumann and Topel, 1991; Malizia and Ke, 1993 Izreali and

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[10] Note that in the census data, the census asked whether you moved from another MSAs over the past 5 years and if so where you have moved from. On the other hand, the ACS data provides annual changes in the mobility of households. To test if the results change due to these differences, we run the same test from 1980 to 2000 period and 2005 to 2011 period but found no noticeable changes in the results.

Murphy, 2003) find that areas with greater industrial diversity have lower unemployment rates as workers are able to switch to a firm in another industry when the job market condition in their own industry turns negative. We hypothesize that the low skilled people are likely to benefit more from greater industrial diversity as they are less likely to possess skills that are firm specific and thus can move easily to another job in highly diversified areas. On the other hand, highly skilled people may benefit more in areas with greater industrial concentration as they may benefit from greater spillover effects by interacting with those with similar skill sets. This is the basic story of agglomeration. Thus, the level of inequality is expected to be lower in areas with higher industrial diversity.

We use two proxies of industrial diversity: 1) national average index and 2) portfolio variance index. To calculate these proxies, we use employment data from the County Business Patterns (CBP)[11]. The national average index is measured by the following equation:

$$\mathrm{NA} = \sum_{i=1}^{N} \frac{(X_i - \overline{X_i})^2}{\bar{X}_i} \tag{2}$$

where X_i is the *i*th industry's share of employment in the MSA, $\bar{X}_i$ is the national average employment share in the *i*th industry and N is the number of industries in the MSA. The index measures the how the regional employment percentages in each industry deviates from the national averages. The index is based on location quotients (Siegal, Johnson and Alwang, 1995) and the value increases as the MSA becomes more specialized. A MSA that is perfectly representative of the national economy would get an index value of zero.
The portfolio variance index is borrowed from the finance theory and is currently the most commonly used measure of industrial diversification (Dissart, 2003). The advantage of this index is that it incorporates the interrelationship between the industries. The index is calculated by the following equation.

$$\mathrm{PV} = \ln\left(\sum_{i=1}^{N} W_i^{\,2} VAR(X_i) + \sum_{i=1}^{N}\sum_{j=1, j\neq i}^{N} W_i W_j COV(X_i, X_j)\right) \tag{2}$$

where W_i and W_j are the shares of employment in industry i and j in a region, $VAR(X_i)$ is the employment variance of industry i, and $COV(X_i, X_j)$ is the employment covariance of industry i and j. N again is the number of industries. The variance and covariance matrix for the this index is estimated using annual data from 1990 through 2011.Similar to the NA index, a higher PV index means a lower level of industrial diversity or a greater level of specialization.

Other MSA Variables

In addition to the above explanatory variables we include the percent of union members in each MSAs. Card (2001) show that the decline in unionization is an important factor

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[11] In 1997, the Standard Industrial Classification (SIC), which classified industries into four digit codes, was replaced by the North American Industry Classification System (NAICS). NAICS also was revised in the years of 2002, 2007 and 2012. Thus, to obtain a comparable diversity indices we match the two classification systems by the first two digits of the SIC codes. Both diversity indices are calculated at the two digit level.

explaining the increase in income inequality. Our unionization data come from the Bureau of Labor Statistics. We also include the log value of median income, mean house value and MSA population as regressers; these are calculated from the Census and the ACS. Studies, including Glaeser et al. (2009) and Baum-Snow (2013), find that larger cities tend to be more unequal.

Explanatory Variables: State Level

State level variables include three proxies of unemployment insurance benefits, minimum wage, two political variables and January temperature. These variables are matched to each MSA. Also for MSAs which are located in multiple states, we assign the weighted average of the state level variables using the share of MSA population living in each state.

Unemployment insurance programs provide financial benefits to people who are unemployed. The three measures we use in the paper are the minimum and the maximum amount of weekly benefits, and the minimum amount of weeks that the benefits are provided. We do not include the maximum weeks as in almost all states this value is 26 weeks. The data is collected from the U.S. Department of Labor. Another variable we use is the amount of minimum wage, which is also from the Department of Labor. For states where this data is not available or for those with minimum wage lower than the federal rate, we designate the federal amount, which is the legally binding amount. If these policies are effective, we will observed that states that offer more generous UI benefits and higher minimum wages will experience smaller increases in inequality over time.

The political variables are defined by both the proportion of Senate and House representatives for each party in each state. We define blue states as those with two Democratic Senators, red states as those with two Republican Senators and purple states as those with one Senator from each party. We also create a color variable which equals zero for red states, one for purple states and two for blue states. For this variable, we obtained the data from the U.S. Senate homepage[12]. Percent of Democrats are percent of votes the Democratic Party received in the most recent congressional election and is collected from the Office of the Clerk of the U.S. House Representatives[13] Finally, we obtain the January temperature data from the National Climate Data Center (NCDC).

Summary Statistics

Table I presents the summary statistics for all the dependent and explanatory variables. On average, the income level ratio of top 10th percentile to bottom 10th percentile is 11.09. As expected, the standard deviation for the top ten percent is greater than for the bottom ten percent. Sixty-six percent of the adult population participate in the labor market and the average unemployment rate is 8 percent. The average percentage of adult population with a BA degree is 29 percent, which is 16 percent higher than the share of high school drop-outs. The mean mobility rate of those with a BA degree is 2 percent higher than those who drop-

[12] www.senate.gov
[13] clerk.house.gov/member_info/electioninfo/

out from high school. Blacks accounts for 14 percent of the population, while Hispanics and Asian accounts for 17 and 5 percent, respectively. Among the dissimilarity indices, black-white index shows the highest average, indicating the level of segregation is greatest between the two groups. Due to the nature of the calculation, the mean of the national average industrial diversity index is lower than the portfolio variance index, but has greater variance. The average median income is slightly above 50,000 dollars and the average mean house value is around 277,000 dollars with a large standard deviation. The average population of MSAs also shows a great deal of variance[14].

As for the state level variables, we find that the minimum weekly unemployment insurance is 49.50 dollars while the maximum is 390.61 dollars. The average minimum weeks of receiving the unemployment insurance benefit is 14.63 weeks. The mean value of the nominal minimum wage is 6.49 dollars. In our analysis, 47.1 percent of people live in blue states, while 25.5 percent reside in purple states. The Democratic Party on average received 48.1 percent of votes in the congressional elections during 1990-2011. Finally, the average value of January temperature is 35.20 Fahrenheit.

IV. Results

<u>Level of City Inequality 1990-2011</u>

Labor Market Condition& Skill Composition

Table II shows the result of the base model, where we include independent variables related to labor market conditions, skill distribution and mobility[15]. The dependent variable in the first two columns is the difference in the log of income for the top and the bottom 10th percentiles, which is the proxy for the city's income inequality. The third and the forth columns present the results using the log real income of the top 10th percentile as the dependent variable, and the final two columns show the results where the dependent variable is the log real income of the bottom 10th percentile. In all of the following tables, the regression results will be presented in the same order.

The results show that cities with higher labor participation rates and lower unemployment rates have more equality. This is because the real income of the bottom 10th percentile is higher in cities with better labor market conditions while the real income of the top 10th percentile is less affected by the labor market environment. In fact, when we include the state and year fixed effects, we find that the income of the top 10th percentile is higher in

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[14] In all the regressions, three proxies of income distribution, population, median income and mean house values are used in log terms. Also the net mobility rate are used in the regression analyses. All regressions are weighted by the population of each MSA.

[15] The independent variables of the base model are included in all of the following regressions. As we find almost no changes in the signs and the statistical significance of the coefficients of these variables, we do not report them in the subsequent tables.

cities with lower labor participation rate and higher unemployment rate.

Next, we find that inequality is greater in cities with greater shares of adults with a Bachelor degree. The inequality is also higher in areas with higher high school drop-outs shares. MSAs with greater share of those with a BA degree have higher average income levels for the top 10^{th} but lower average income levels for the bottom 10^{th} percentile. Although further investigation is needed, the findings accord with the skill bias technological change hypothesis. In other words, the MSAs where technological improvements have had the greatest local impact are likely the MSAs with higher shares of skilled labor, i.e., BAs. On the other hand, the income level of the top 10^{th} percentile is also higher in MSAs with greater share of high school drop-outs while the income of the bottom 10^{th} is lower also in these areas. This may be related to the fact in areas with greater share of high school drop-outs there are less high school graduates who may be able replace the work of the BA graduates. Thus, the BA degree is more valuable as there are fewer substitutes. The income of the bottom 10^{th} percentile may be lower in MSAs with greater share of high school drop -outs due to a greater competition among the lowest skilled workers.

MSAs where the net mobility of population with a BA degree is high have low levels of inequality, as it turns out because these MSAs have higher levels of income for the bottom 10^{th} percentile. Meanwhile, greater shares of high school drop-outs are moving to areas where the income level of the top 10^{th} percentile is higher. This contradicts the general perception that BA degree holders are moving into areas where the returns to skills are higher. In the long run, however, the migration of skilled workers should not affect the income levels at the top, as the increase in the supply of skilled workers puts downward pressure on wages, and thus reduces the return to skill.

Cities with higher median incomes have lower inequality. The top and the bottom 10^{th} percentile both have higher income in places with higher median income, but the positive magnitude is greater for the bottom 10^{th} percentile. The income level in cities with higher average house values is higher for the top 10^{th} percentile and lower for the bottom 10^{th} percentile, and thus income inequality is higher in these areas. This agrees with the findings of Ganong and Shoag (2014), who finds that high house prices inhibit low income workers from in-migration moving into these area even when the labor market condition is better than other areas, while the high income workers can easily move to the areas with better job opportunities.

We confirm previous studies (Glaeser et al., 2009; Snow-Baum, 2013) that larger cities have more inequality. While the income level for the top 10^{th} percentile is higher in larger cities, it is lower for the bottom 10^{th} percentile when we control for the state and year fixed effects.

Racial Composition & Segregation

Next we investigate how MSAs' racial composition is related to the level of income inequality. Table III shows that cities with greater shares of black population are less equal. In these cities the income of the bottom 10^{th} percentile is significantly lower while those in the top 10th percentile is higher[16]. This shows that in places with greater shares of black laborers, low income households earns less. In a glance, it is unclear why the top income households have higher income in areas with higher black shares. If we include the segregation index and the interaction term, however, the statistical significance for the share of black variable disappears. The results including the dissimilarity index show that MSAs with greater racial segregation of blacks have higher top 10th percentile income. Furthermore, the income of the top 10th percentile is even higher in MSAs with both higher share of blacks and higher level of black-white segregation. This means high income populations earn more in areas where the black-white segregation is greater. One possible explanation for these findings is that higher income people are benefiting more from the spatial match of jobs or social interaction effect in areas with greater concentrations of white population.

Meanwhile, the relationship between inequality and the share of Hispanic or Asian population do not show a consistent pattern across the columns. MSAs with a greater segregation of Hispanics have lower show income level of the top 10th percentile, while this relationship opposite for the Asian-white segregation index. The result of the interaction term shows that income inequality is higher in areas with greater racial segregation of Hispanics and at the same time has greater share of Hispanic population. In these MSAs, the top 10th percentile has higher incomes while the opposite holds for the bottom 10th percentile.

Industrial Diversity & Unionization

Next, we investigate whether industrial diversity and unionization are related to cities' income inequality. The findings in Table IV show that the portfolio variance measure of industrial diversity does not show a statistically significant relationship with any of the three dependent variables. On the other hand, the National Average Index shows a statistically positive relationship with the level of inequality: cities with greater levels of industrial specialization have higher levels of inequality. In these MSAs, the income of the top 10th percentile is higher. Meanwhile, the income of the bottom 10th percentile do not show a statistically significant relationship with specialization. This agrees with our hypothesis that implies higher income households benefit more in areas with greater levels of specialization due to human capital spillover. While lower income households also benefit from the human capital spillover effect, they may at the same time be worse off in specialized places as they face greater difficulty of finding a new job when they are laid off (Chinetz, 1961). These offsetting impact may lead to a zero net effect of specialization on incomes for the bottom decile.

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[16] Note that in our data, 63.7 percent are white households and 14.0 percent are blacks. However, white households account for 82.3 percent of those above the top 10th income percentile, while black accounts for only 3.8 percent. On the other hand, 59.5 percent of those below the bottom 10th income percentile are white and 20.0 percent are black households. This shows that relative to the total population distribution, relatively greater proportion of whites are in the top 10th income percentile while relatively less proportion of blacks are in this category. Opposite holds for the bottom 10th income percentile

On the other hand, the share of union members is positively associated with the level of income inequality. This is because the income level of the bottom 10^{th} percentile is lower in MSAs with higher share of union members, while the income level of the top 10^{th} percentile is not associated with the percent of union members. This result may reflect that MSAs with low incomes at the bottom 10^{th} percentile will be more likely to have more union members, but does not show how union members affect changes in the income of bottom 10^{th} percentile. As we shall see, places with higher levels of unionization saw smaller increases in inequality.

State Level Variables

Finally, we investigate how the state level variables are associated with the three dependent variables (Table V). Here the regressions cover the period of 2000-2011, as we have the unemployment insurance benefit data starting from the year 2000. In columns (1), (3), (5) we do not include the state and the year fixed effects, in order to identify the relationship between the actual level of the state variables and the dependent variables. In columns (2), (4), (6) we include both the state and the year fixed effects. In these regressions the coefficients shows the relationship between the changes in the state variables and the three proxies of income distribution.

The results show that MSAs in states with higher amount of minimum and maximum weekly unemployment insurance benefits and longer period of minimum weeks receiving the benefits have greater level of inequality. Also, the income of the bottom 10^{th} percentile is lower in these MSAs. It is difficult to draw any causal relationship from these results since the regression only demonstrates correlation. This merely implies that MSAs with greater inequality and lower income level for the bottom 10^{th} percentile give greater weekly benefits for more weeks on average. When the state and the year fixed effects are included, we find that an increase of minimum weekly benefits is associated with lower income inequality and higher level of income for the bottom 10^{th} percentile. Although further investigation is needed, this suggests that unemployment insurance may have some positive impact on lowering income inequality by increasing the income for those in the lower end of income distribution. The level of minimum wage is negatively associated with both the income level of the top and bottom 10^{th} percentile. The change in the minimum wage, however, does not show any statistical association with any of the three dependent variables.

Blue and Purple states do not show any statistical differences in the level of income inequality compared to Red states. However, both income of the top and the bottom percentiles are higher in Blue and Purple states. This is related to the fact that most of the Red states are located in the central part of the US, which are relatively poor. States with greater shares of voted for Democratic house candidates also have higher levels of income at the bottom 10^{th} percentile. The changes in the share of Democratic Senates or the House representatives do not show any statistical association with the income distribution. Finally, MSAs in states with higher January temperature have lower inequality levels, because the income of the bottom 10^{th} percentile is higher in these areas. The size of the coefficient, however, is close to zero, indicating that temperature has negligible relationship with the income inequality.

Changes in City Inequality: 1980-2011

The next sets of regressions investigate variables associated with changes in inequality over time. Here we expand our data back to the year 1980 to include the changes inequality from 1980 to 1990, and contrast that period with others. The dependent variables, which are now in changes, show the changes from the previous to the current period, while variables that are in levels are values from the previous period. In all regressions, the dependent variables are 1) the changes in the measure of income inequality, 2) the changes in log real income of the top 10^{th} percentile, and 3) the changes in the log real income of the bottom 10^{th} percentile.

Labor Market Condition & Skill Distribution

Table VI presents the result of the base model, which includes variables related to the labor market condition and skill distribution[17]. The result shows that the income level of both top and bottom 10^{th} percentiles show greater increases in MSAs with higher labor participation rates. Since the rate of the increase is similar for the two groups, the impact of the labor market variables on changes in the measure of inequality is not significant at standard measures of statistical significance. Income levels at both the 90th and 10^{th} percentile show less increase in areas with higher levels of lagged unemployment, but the unemployment rate also show no statistically significant relationship with the changes in the level of inequality. Meanwhile, the level of inequality decreases in areas where the labor participation rate increases, as the relative income level increase is higher for the bottom than the top 10^{th} percentile. Increases in the level of unemployment decreases the level of income for both rich and the poor, but the rate of decrease is higher for the bottom 10^{th} percentile. Thus, inequality rises in areas that experience greater increase in unemployment. These findings suggest that although both high-income and low-income households are negatively influenced when labor market conditions turn negative, the low-income households are affected by a greater magnitude. This results accords with our hypothesis, which suggests high skilled people are more difficult to hire and fire due to their firm-specific skills. Following the recent housing market crisis, the national unemployment rate rose more than 5 percentage points while the labor participation rate decreased. As a result, low skilled labor disproportionately lost jobs, which explains why the level of inequality increased since 2007 while the real income decreased for both the rich and the poor.

In our regression results, we also find that the share of adults with a Bachelor degree and the share of high school drop-outs are not associated with the changes in the three proxies of income distribution. These variables, however, may have different association with the changes in inequality over time and thus we will require further investigation. Meanwhile, MSAs with net increases of the BA population show an increase in the income level for both

[17] These variables are included in all the following regressions but again the results are not presented in the next three regressions as they do not show significant differences from the results in Table XX.

top and the bottom 10^{th} percentile. On the other hand, the income of top and the bottom 10^{th} percentile increases in MSAs where there is a net decrease in the mobility of high school drop-outs. There are two possible explanations for these results. First, high skilled labor is creating spillover effects in MSAs they enter, resulting in an increase in real income in those areas. It is also possible that high skilled labors are moving into areas where their real income level is likely to increase. An inflow of high skilled labors may increase the cost of living in those areas, causing high school drop-outs to move to areas with lower costs of living.

MSAs with higher median income show less increase in both the income level of the top 10^{th} and the bottom 10^{th} percentile, indicating that income level across MSAs are gradually converging over time. House values do not have any significant relationship with the changes in the income distribution. Finally, in contrast to Baum-Snow (2013), the income inequality in cities with larger populations *decreased*, as the income of level of the bottom percentile increased more than the income level of the top percentile. The different findings may be due to the different data used to calculate inequality – while Baum-Snow (2013) focuses on wage inequality of working age males, we look at the income inequality at a household level.

Racial Composition & Segregation

Table VII presents how racial composition and segregation is associated with the changes in the income distribution. We find that MSAs with greater shares of black households experienced a greater increase in the income level at both the top and bottom 10^{th} percentile.

However, when we control for segregation, these relationships disappear. In fact, we observed that MSAs with higher shares of blacks show less increase in the income level of the top 10^{th} percentile. Consistent with the results from Table III, we observe that the income of the top and the bottom increase more in more segregated MSAs with greater proportions of blacks. Although further examination is required, this could be due to the fact that black-white segregation produces greater benefits to white households residing in these MSAs due to greater interaction among themselves. There could also be greater level of unobserved discrimination in these areas, which works favorably for the high income population.

Share of Hispanic population and the segregation of Hispanics do not show a significant relationship with the changes in the three proxies of income distribution. Meanwhile, places with more Asians show a greater increase in the income level of both top and bottom 10^{th} percentile. This is likely due to several unique characteristics of Asians who have recently became the fastest-growing racial group in the United State. Compared to other race groups, Asians have highest level of education and income. Asian immigrants show a fastest increase in the level of income after coming to the US (Pew, 2013), which explains why areas with more Asians experience an increase in the income level for both income groups.

Industrial Diversity & Unionization

Table VIII displays the results of regressions that include industrial diversity and unionization as explanatory variables. In all regression, we find that the level of industrial diversity is not associated with the changes in the level of income distribution. On the other hand, MSAs with greater share of union members show less increase in the level of inequality. The income level of those in the 10th percentile increases more where the percent of union members are higher. This finding is consistent with the previous studies that attribute the rise in inequality to the decline in unionization.

State Level Variables

Finally, we investigate how the state level variables affect the changes in the income distribution (Table IX). Among the variables characterizing unemployment insurance benefits, the maximum amount of weekly benefits have a negative relationship with the changes in the income inequality. MSAs that provide higher maximum unemployment benefits show a higher increase in the income level for both top and the bottom 10th percentile but the increase is greater for the bottom 10th percentile. Together with the findings from the previous regressions (Table V), the results suggest that unemployment insurance programs do provide some economic benefits to lower income households and thereby decrease income inequality.

Meanwhile, minimum wage and the political color of the state have no relationship with the change in the income distribution. MSAs with greater share of Democratic House Representatives experience a decrease in the level of inequality as the income level of the bottom 10th percentile increases more in these places. Again, January temperature does show some statistical significance in the regression results, but the size of the coefficient is close to zero.

<u>Changes in City Inequality in Different Time Periods: Boom & Bust</u>

The final sets of regressions investigate whether skill and racial composition have different relationships with the changes in the income distribution in different time periods. We classify the time periods into the following three 1) 1980-2000: economic growth period when the average inequality increased with an increase of income levels of both the top and the bottom 10th percentiles 2) 2005-2007: housing boom period when average inequality decreased and 3) 2008-2011: housing bust period when the average inequality increased while the income level of both the top and the bottom 10th percentiles fell. For these analyses, we adopt a difference in differences framework.

Skill Distribution: 1980-2000, 2001-2007, 2008-2011

In Table VI, we showed that the share of BAs or high school dropouts have no relationship with the changes in inequality. However, it is possible that the skill distribution has different associations with income inequality in different time periods. Thus, in Table X we break the sample into three periods using two year dummies and further investigate the relationship between the skill and income distributions.

In accordance with Glaser et al. (2009), we find that the share of BAs is positively associated with the change in income inequality between 1980 and 2000. In MSAs with greater shares of BAs, the income level of the top 10th percentile showed increased more than the income level of the bottom 10th percentile, although both did increase. Similarly, inequality in places with higher shares of high school drop-outs increased more as the income growth of the bottom 10th percentile was lower than growth of the top 10th percentile. This may be related to the fact that low skilled labor can be easily replaced in the areas with abundant supply of these workers, which suppressed their wage increase.

This relationship reversed during the housing boom when the level of inequality slightly decreased. During this period, inequality rose less in MSAs with a greater share of BAs and high school drop-outs. The MSAs with higher shares of Bachelor degrees show less increase in the income level of the top 10th percentile but a greater increase in that of the bottom 10th percentile. The income of the bottom 10th percentile grew more in places with proportionately more high school drop-outs. One plausible explanation for these changes is the diffusion of technology. During the 1980-2000 period, skilled biased technology is likely to have changed most in MSAs with higher shares of BAs. In the following periods, however, these technological improvements would have spilled over to other areas. Another possible explanation is that over time, both high skilled and low skilled workers moved to places where the return for skill is higher. Thus, owing to the diffusion of technology and the migration of households, the relationship between income inequality and skill distribution reversed in the 2000s compared to the relationship in the 1980s and 1990s.

Finally, in the period following the crisis, we observed that the relationship between skill composition and income distribution become significantly weaker, although we find that the income of the bottom 10th percentile increased less in MSAs with a larger share of BAs.

Racial Composition: 1980-2000, 2001-2007, 2008-2011

Finally, we look at the relationship between racial composition and income distribution in three different time periods. It is well documented that low income and minority households received greater access to the mortgage market during the housing boom. (Schwartz, 2010). Increases in the house prices were associated with a decrease in unemployment and increase in labor participation.[18] The channel for this was the construction industry. Thus, during the housing boom, the income level of the low income households may have increased more rapidly than the income of high income white households.

Table XI shows that during the housing boom, MSAs with greater shares of Hispanics and Asians experienced a greater increase in the income level of the bottom 10th percentile. Prior

[18] If we regress the change in house price on change in unemployment and labor participation we find the coefficient of the change in unemployment is negative and the coefficient of the change in labor participation is positive. Both variables are significant at 1% level.

to the crisis, however, we do not find any relationship between black population share and changes in income levels.

Since 2008, however, labor market conditions worsened most in places that experienced the greatest drops in the house prices (Mian & Sufi, 2014). Many of these markets has high minority populations. The regression results Table XI show that from 2008, the MSAs with greater proportion of black households showed a greater increase in inequality. Since 2008, the income level of the bottom 10th percentile fell more in MSAs with greater percent of blacks. Meanwhile, the share of Asian and Hispanic households do not show a significant relationship with the changes in the income distribution.

V. Conclusion

This study investigates the differences in the level and the changes in the level of inequality across MSAs over the past 30 years. Our regression analysis shows that the level of income inequality is greater in MSAs with negative labor market conditions, better educated populations, higher racial segregation and greater industrial specialization. As for the changes in the level of inequality, we find that that negative changes in the labor market conditions increase inequality, as the real income of the poor falls relatively more than that of the rich. We also find that between 1980 and 2000, share of high skilled labor had a positive relationship with the changes in income inequality, but this relationship reversed in the following years. During the housing boom, MSAs with greater shares of Hispanic and Asian households experienced a greater increase in the income level of the bottom 10th percentile. Following the bust, the real income of the bottom 10th percentile dropped more in areas with greater proportions of blacks. Finally, among the institution and policy variables, our findings show that unionization and unemployment insurance benefit programs has some level of effectiveness in reducing income inequality.

So far, analysis does not nail down causal relationships. In the future, we plan to improve our paper by using instrumental variables or external shocks to better identify how the inequality of income is influenced by the multiple explanatory variables used in our study.

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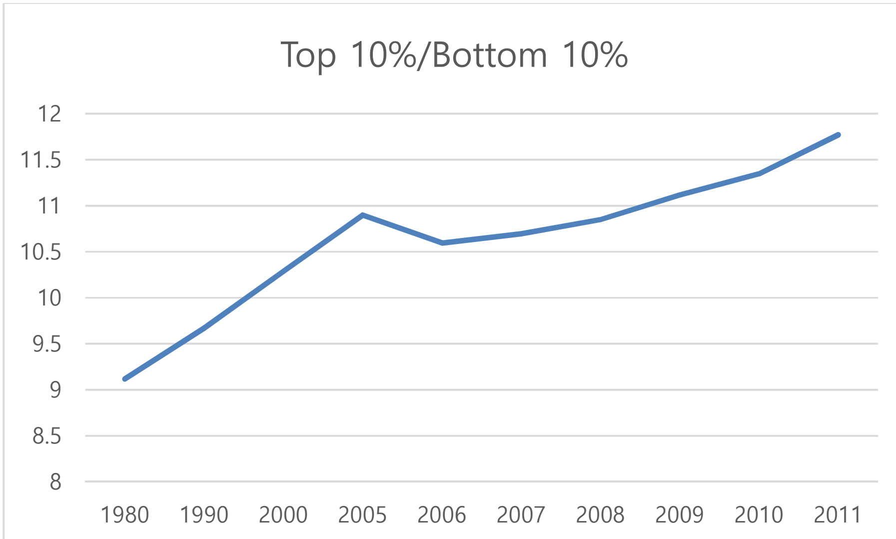
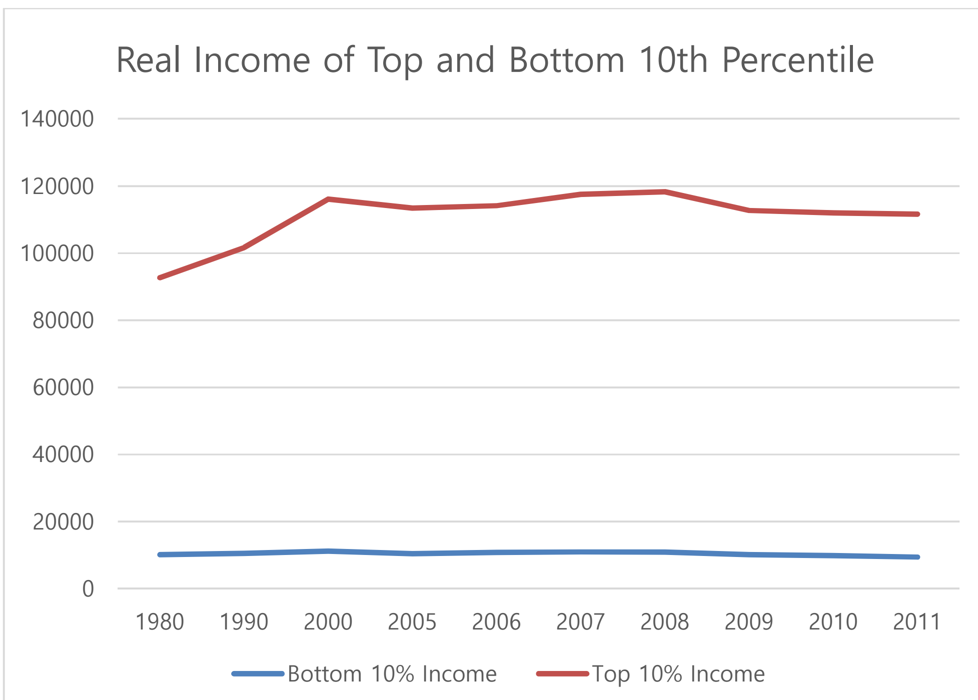
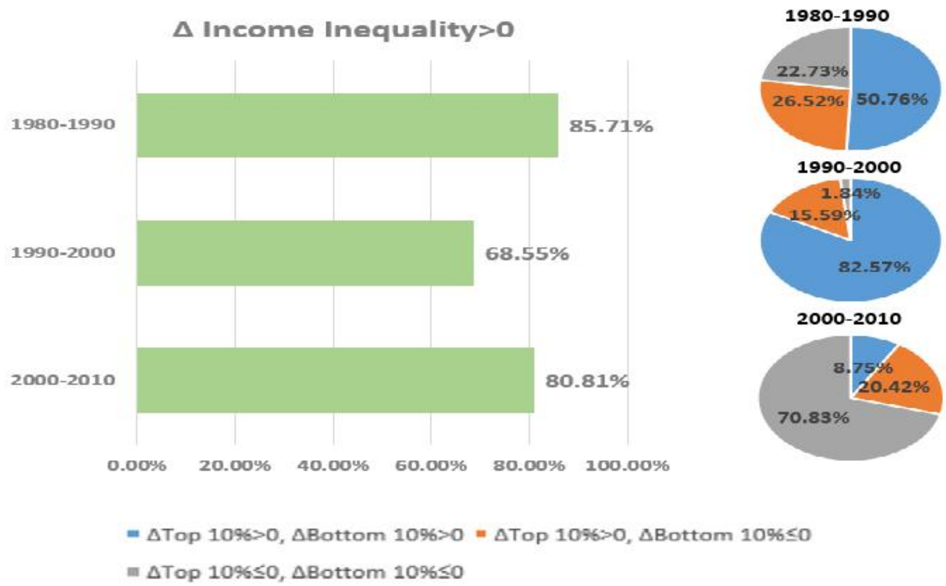
Tables and Figures



[Figure I] Income Level of Top 10th Percentile over Bottom 10th Percentile



[Figure II] Income Level of Top & Bottom 10th Percentile



[Figure III] Percent of MSAs: Positive Increase in Inequality

[Table I] Summary Statistics

Variable	Obs	Mean	Std. Dev.
Dependent: Inequality & Income			
Top 10%/Bottom 10%	2570	11.059	2.12
Top 10%	2570	113428	22489
Bottom 10%	2570	10469	2219
Explanatory: MSA Levels			
Labor Participation Rate	2570	0.661	0.04
Unemployment Rate	2570	0.078	0.03
% Bachelor (BA)	2570	0.290	0.07
% High School Dropouts	2570	0.134	0.05
BA: Mobility Rate	2438	0.062	0.06
HS: Mobility Rate	2438	0.035	0.03
% Black	2570	0.140	0.10
% Hispanic	2570	0.169	0.16
% Asian	2570	0.054	0.06
Dissimilarity: Black	2237	0.621	0.13
Dissimilarity: Hispanic	2237	0.396	0.13
Dissimilarity: Asian	2237	0.390	0.07
Portfolio Variance	2082	26.206	0.62
National Average	2082	0.490	1.14
% Union Members	1828	0.121	0.069
Median Income	2570	50330	11142
Mean House Value	2570	277308	161322
Population	2570	2766911	2805584
Explanatory: State Levels			

Min (Wage Benefit)	2224	49.496	22.72
Max(Wage Benefit)	2224	390.615	101.67
Min(UI Week)	2224	14.653	6.15
Minimum Wage	2551	6.493	1.20
Blue	2570	0.471	0.50
Purple	2570	0.255	0.44
% Democrats	2553	0.482	0.16
January Temperature	2535	36.260	11.94

[Table II] Inequality: Labor Market Condition & Skill Distribution

	ln(Top 10%/Bottom10%)		ln(Top 10%)		ln(Bottom 10%)	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
MSA: Basic						
Labor Participation Rate	-1.832***	-1.266***	-0.289***	-0.486***	1.544***	0.781***
	(0.150)	(0.135)	(0.0903)	(0.0528)	(0.154)	(0.110)
Unemployment Rate	1.482***	1.587***	-1.266***	0.477***	-2.748***	-1.110***
	(0.152)	(0.200)	(0.0842)	(0.0657)	(0.160)	(0.174)
% BA+	1.910***	1.570***	1.091***	0.736***	-0.819***	-0.834***
	(0.0990)	(0.0758)	(0.0539)	(0.0275)	(0.100)	(0.0647)
% HS -	1.011***	0.686***	0.948***	0.383***	-0.0635	-0.303***
	(0.0984)	(0.0954)	(0.0671)	(0.0328)	(0.105)	(0.0787)
BA+ Net Mobility	-0.628***	-0.191***	0.0779	0.0419*	0.706***	0.233***
	(0.0883)	(0.0621)	(0.0613)	(0.0225)	(0.107)	(0.0542)
HS- Net Mobility	-0.0693	-0.0294	-0.176***	-0.0496*	-0.107	-0.0202
	(0.0921)	(0.0700)	(0.0682)	(0.0281)	(0.110)	(0.0594)
Ln(Median Income)	-0.209***	-0.505***	0.383***	0.672***	0.592***	1.177***
	(0.0447)	(0.0422)	(0.0284)	(0.0155)	(0.0513)	(0.0354)
Ln(Mean House Value)	0.0389**	0.177***	0.0285***	0.0872***	-0.0104	-0.0903***
	(0.0170)	(0.0152)	(0.0110)	(0.00594)	(0.0185)	(0.0125)
ln(Population)	0.0205***	0.0254***	0.0300***	0.0146***	0.00948**	-0.0107***
	(0.00423)	(0.00279)	(0.00292)	(0.00118)	(0.00405)	(0.00246)
Constant	4.863***	6.050***	6.217***	3.413***	1.354***	-2.637***
	(0.345)	(0.317)	(0.179)	(0.114)	(0.358)	(0.271)
State FE	N	Y	N	Y	N	Y
Year FE	N	Y	N	Y	N	Y
Observations	2,438	2,422	2,438	2,422	2,438	2,422
R-squared	0.543	0.737	0.843	0.962	0.604	0.855

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[Table III] Inequality: Racial Composition & Segregation

	ln(Top 10%/Bottom10%)			ln(Top 10%)			ln(Bottom 10%)		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MSA: Race & Segregation									
% Black	0.825***	0.832***	0.826***	0.160***	0.182***	0.0502	-0.665***	-0.650***	-0.776***
	(0.0488)	(0.0491)	(0.197)	(0.0169)	(0.0160)	(0.0651)	(0.0440)	(0.0446)	(0.183)
% Hispanic	0.00615	0.0801	-0.286***	-0.0254	0.0377**	-0.0463	-0.0315	-0.0423	0.240***
	(0.0503)	(0.0632)	(0.0793)	(0.0171)	(0.0184)	(0.0302)	(0.0444)	(0.0574)	(0.0708)
% Asian	0.375***	0.237**	0.131	0.0294	0.108**	0.0897*	-0.346***	-0.130	-0.0413
	(0.100)	(0.115)	(0.118)	(0.0513)	(0.0481)	(0.0478)	(0.0764)	(0.0965)	(0.101)
Dissimilarity: Black		-0.00655	-0.111***		0.0964***	0.0380**		0.103***	0.149***
		(0.0376)	(0.0425)		(0.0131)	(0.0161)		(0.0336)	(0.0389)
Dissimilarity: Hispanic		-0.00699	-0.0942***		-0.0277***	-0.0392***		-0.0207	0.0551*
		(0.0270)	(0.0333)		(0.0106)	(0.0123)		(0.0235)	(0.0302)
Dissimilarity: Asian		0.207***	0.284***		0.0399**	0.0772***		-0.167***	-0.207***
		(0.0441)	(0.0623)		(0.0174)	(0.0247)		(0.0404)	(0.0577)
% Black * Dissimilarity Black			0.441			0.410***			-0.0310
			(0.287)			(0.0852)			(0.266)
% Hispanic* Dissimilarity Hispanic			0.852***			0.183***			-0.669***
			(0.166)			(0.0609)			(0.155)
% Asian * Dissimilarity Asian			-0.643*			-0.288**			0.355
			(0.388)			(0.146)			(0.347)
Constant	6.053***	6.073***	5.683***	3.490***	3.864***	3.832***	-2.563***	-2.208***	-1.851***
	(0.290)	(0.340)	(0.352)	(0.125)	(0.125)	(0.128)	(0.257)	(0.307)	(0.320)
Basic Control	Y	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,422	2,117	2,117	2,422	2,117	2,117	2,422	2,117	2,117
R-squared	0.786	0.794	0.798	0.964	0.969	0.969	0.879	0.877	0.879

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[Table IV] Inequality: Industrial Diversity & Unionization

	Δln(Top 10%/Bottom10%)			Δln(Top 10%)			Δln(Bottom 10%)		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MSA: Industrial Diversity									
Portfolio Variance Index	0.00659			0.00121			-0.00538		
	(0.00486)			(0.00149)			(0.00411)		
National Average Index		0.00497**			0.00181**			-0.00316	
		(0.00253)			(0.000871)			(0.00200)	
MSA: Unionization									
			0.276***			0.0287			-0.247***
			(0.0801)			(0.0276)			(0.0683)
Constant	6.327***	6.529***	5.886***	4.224***	4.268***	3.751***	-2.103***	-2.261***	-2.135***
	(0.455)	(0.419)	(0.383)	(0.141)	(0.128)	(0.132)	(0.382)	(0.359)	(0.334)
Basic Control	Y	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,969	1,969	1,699	1,969	1,969	1,699	1,969	1,969	1,699
R-squared	0.672	0.672	0.701	0.951	0.951	0.962	0.844	0.844	0.869

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[Table V] Inequality: State Level Variables

VARIABLES	ln(Top 10%/Bottom10%)		ln(Top 10%)		ln(Bottom 10%)	
State						
Min (Wage Benefit)	0.000246	-0.000326	-4.63e-05	0.000173	-0.000292**	0.000499*
	(0.000154)	(0.000358)	(7.06e-05)	(0.000127)	(0.000134)	(0.000302)
Max(Wage Benefit)	0.000290***	6.06e-05	-2.65e-05	-3.23e-05	-0.000317***	-9.29e-05
	(4.25e-05)	(0.000113)	(1.95e-05)	(3.24e-05)	(4.08e-05)	(9.54e-05)
Min(UI Week)	0.00335***	0.00228*	0.000355	0.00112**	-0.00299***	-0.00116
	(0.000637)	(0.00129)	(0.000332)	(0.000514)	(0.000611)	(0.00104)
Minimum Wage	-0.00824	-0.00331	-0.0451***	-0.00547	-0.0369***	-0.00216
	(0.00638)	(0.00993)	(0.00281)	(0.00355)	(0.00546)	(0.00843)
Blue	-0.0210**		0.0455***		0.0665***	
	(0.0102)		(0.00524)		(0.00943)	
Purple	-0.0178*		0.0198***		0.0377***	
	(0.00954)		(0.00423)		(0.00892)	
Color		0.00532		-0.00130		-0.00662
		(0.00544)		(0.00180)		(0.00483)
% Democrats	-0.0796**	0.0200	0.00439	0.00502	0.0840***	-0.0150
	(0.0382)	(0.0307)	(0.0177)	(0.0119)	(0.0322)	(0.0254)
January Temperature	-0.00153***	0.000861	-5.27e-05	0.000342	0.00148***	-0.000519
	(0.000536)	(0.000966)	(0.000203)	(0.000359)	(0.000492)	(0.000825)
Constant	6.320***	5.898***	4.004***	3.223***	-2.316***	-2.676***
	(0.399)	(0.330)	(0.200)	(0.128)	(0.317)	(0.287)
Basic Contol	Y	Y	Y	Y	Y	Y
State FE	N	Y	N	Y	N	Y
Year FE	N	Y	N	Y	N	Y
Observations	2,084	2,084	2,084	2,084	2,084	2,084
R-squared	0.598	0.734	0.916	0.961	0.761	0.859

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[Table VI] ΔInequality: Labor Market Condition & Skill Distribution

	Δln(Top 10%/Bottom10%)	Δln(Top 10%)	Δln(Bottom 10%)
VARIABLES	(1)	(2)	(3)
MSA: Basic			
Labor Participation Rate	-0.0524	0.301***	0.353***
	(0.0955)	(0.0679)	(0.0904)
Unemployment Rate	0.0321	-0.175**	-0.207
	(0.149)	(0.0689)	(0.155)
ΔLabor Participation Rate	-1.985***	0.519***	2.504***
	(0.157)	(0.126)	(0.214)
ΔUnemployment Rate	1.483***	-0.496***	-1.979***
	(0.199)	(0.140)	(0.192)
% BA+	0.0853	0.0537	-0.0317

	(0.0570)	(0.0360)	(0.0543)
% HS -	0.0936	-0.0519	-0.146**
	(0.0630)	(0.0432)	(0.0701)
BA+ Net Mobility	-0.0597	0.169***	0.229***
	(0.0551)	(0.0483)	(0.0590)
HS- Net Mobility	-0.00746	-0.126***	-0.119*
	(0.0623)	(0.0440)	(0.0709)
Ln(Median Income)	0.0924***	-0.111***	-0.204***
	(0.0341)	(0.0259)	(0.0339)
Ln(Mean House Value)	-0.0278**	0.00360	0.0314***
	(0.0118)	(0.00660)	(0.0117)
ln(Population)	-0.0891**	0.0835*	0.173***
	(0.0390)	(0.0447)	(0.0379)
Constant	-0.167	0.906***	1.073***
	(0.261)	(0.213)	(0.245)
Year FE	Y	Y	Y
State FE	Y	Y	Y
Observations	2,577	2,577	2,577
R-squared	0.252	0.596	0.436

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[Table VII] ΔInequality: Racial Composition & Segregation

	Δln(Top 10%/Bottom10%)			Δln(Top 10%)			Δln(Bottom 10%)		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MSA: Race & Segregation									
% Black	-0.00575	0.00142	0.0433	0.0689***	0.0934***	-0.120*	0.0746**	0.0920**	-0.164
	(0.0366)	(0.0434)	(0.149)	(0.0210)	(0.0249)	(0.0710)	(0.0378)	(0.0411)	(0.145)
% Hispan	1.35e-05	-0.00732	0.0283	0.0218	0.0277	0.0415	0.0218	0.0351	0.0132
	(0.0336)	(0.0415)	(0.0817)	(0.0205)	(0.0203)	(0.0400)	(0.0345)	(0.0421)	(0.0839)
% Asian	-0.0580	-0.155	0.222	0.141***	0.148***	1.676***	0.199**	0.303***	1.454***
	(0.0831)	(0.0958)	(0.588)	(0.0489)	(0.0533)	(0.481)	(0.0813)	(0.109)	(0.528)
Dissimilar: Black		-0.0578	-0.0411		-0.0409	-0.0621*		0.0169	-0.0210
		(0.0360)	(0.0444)		(0.0289)	(0.0333)		(0.0373)	(0.0454)
Dissimilar: Hispan		0.0351	0.0452		0.0222	0.0349*		-0.0129	-0.0103
		(0.0309)	(0.0347)		(0.0200)	(0.0206)		(0.0283)	(0.0328)
Dissimilar: Asian		0.0359	0.0632		0.00183	0.0973**		-0.0341	0.0341
		(0.0460)	(0.0628)		(0.0265)	(0.0470)		(0.0440)	(0.0526)
% Black * Dissimilar Black			-0.0740			0.371***			0.445*
			(0.256)			(0.130)			(0.251)
% Hispan* Dissimilar Hispan			-0.0872			-0.0543			0.0329
			(0.179)			(0.0788)			(0.187)
% Asian * Dissimilar Asian			-0.848			-3.447***			-2.599**
			(1.343)			(1.103)			(1.191)
Constant	-0.224	-0.311	-0.283	1.079***	1.278***	1.515***	1.303***	1.589***	1.798***
	(0.278)	(0.327)	(0.350)	(0.225)	(0.267)	(0.289)	(0.259)	(0.305)	(0.307)
Basic Control	Y	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,577	2,060	2,060	2,577	2,060	2,060	2,577	2,060	2,060

R-squared	0.252	0.290	0.290	0.600	0.632	0.644	0.439	0.467	0.470

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[Table VIII]: ΔInequality: Industrial Diversity & Unionization

	Δln(Top 10%/Bottom10%)			Δln(Top 10%)			Δln(Bottom 10%)		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MSA: Industrial Diversity									
Portfolio Variance Index	0.00287			0.00217			-0.000701		
	(0.00350)			(0.00181)			(0.00335)		
National Average Index		0.000841			-0.00056			-0.00140	
		(0.00214)			(0.00078)			(0.00225)	
MSA: Unionization									
% Union Members			-0.130**			0.00514			0.135**
			(0.0646)			(0.0340)			(0.0643)
Constant	-0.666**	-0.597**	-0.507*	0.620***	0.669***	0.552***	1.286***	1.266***	1.059***
	(0.307)	(0.288)	(0.278)	(0.147)	(0.136)	(0.149)	(0.306)	(0.288)	(0.279)
Basic Control	Y	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,955	1,955	1,677	1,955	1,955	1,677	1,955	1,955	1,677
R-squared	0.242	0.242	0.266	0.616	0.615	0.628	0.431	0.431	0.461

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[Table IX] ΔInequality: State Level Variables

	Δln(Top 10%/Bottom10%)	Δln(Top 10%)	Δln(Bottom 10%)
VARIABLES	(1)	(2)	(3)
State			
Min (Wage Benefit)	-0.0313	-0.00927	0.0220
	(0.0198)	(0.00883)	(0.0182)
Max (Wage Benefit)	-0.103***	0.0261**	0.129***
	(0.0270)	(0.0111)	(0.0247)
Min(UI Week)	-0.00580	-0.00593	-0.000134
	(0.00721)	(0.00374)	(0.00680)
Minimum Wage	0.00602	0.000848	-0.00517
	(0.00485)	(0.00221)	(0.00503)
Blue	0.00201	0.00211	0.000102
	(0.0100)	(0.00409)	(0.00993)
Purple	-0.00225	0.00402	0.00628
	(0.00924)	(0.00390)	(0.00904)
% Democrats	-0.0864***	-0.00450	0.0819***
	(0.0250)	(0.0124)	(0.0249)
January Temperature	0.000104	0.00103***	0.000922
	(0.000592)	(0.000245)	(0.000586)
Constant	0.183	0.106	-0.0774
	(0.271)	(0.127)	(0.274)
Basic Control	Y	Y	Y
State FE	Y	Y	Y
Observations	2,035	2,035	2,035
R-squared	0.115	0.247	0.244

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[Table X] ΔInequality: 1980-2000, 2001-2007, 2008-2011 – Skill Distribution

	Δln(Top 10%/Bottom10%)	Δln(Top 10%)	Δln(Bottom 10%)
VARIABLES	(1)	(2)	(3)
MSA: Skill Composition			
% BA+	0.968***	0.316**	-0.651***
	(0.202)	(0.149)	(0.225)
% HS -	0.867***	-0.00749	-0.874***
	(0.148)	(0.141)	(0.178)
Year 2001	0.280***	0.0217	-0.258***
	(0.0731)	(0.0574)	(0.0781)
% BA+ * Year2001	-0.832***	-0.370**	0.462**
	(0.205)	(0.146)	(0.232)
% HS - * Year2001	-0.854***	-0.130	0.724***
	(0.189)	(0.154)	(0.214)
Year2008	-0.0499	0.000585	0.0504

	(0.0336)	(0.0160)	(0.0330)
% BA+ * Year2008	0.138*	-0.0121	-0.150**
	(0.0747)	(0.0365)	(0.0762)
% HS - * Year2008	0.0614	0.0294	-0.0320
	(0.125)	(0.0591)	(0.123)
Constant	-0.228	0.515***	0.743***
	(0.249)	(0.188)	(0.272)
Basic Control	Y	Y	Y
State FE	Y	Y	Y
Observations	2,577	2,577	2,577
R-squared	0.156	0.561	0.293

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[Table XI] ΔInequality: 1980-2000, 2001-2007, 2008-2011 – Racial Composition

	Δln(Top 10%/Bottom10%)	Δln(Top 10%)	Δln(Bottom 10%)
VARIABLES	(1)	(2)	(3)
MSA: Racial Composition			
% Black	0.0502	0.106*	0.0561
	(0.0892)	(0.0568)	(0.0885)
% Hispan	0.0699	0.0373	-0.0326
	(0.0723)	(0.0577)	(0.104)
% Asian	0.425*	0.117	-0.308
	(0.231)	(0.112)	(0.242)
Year2001	-0.00839	-0.0795***	-0.0711***
	(0.0204)	(0.0168)	(0.0203)
% Black * Year2001	-0.101	-0.0527	0.0485
	(0.0938)	(0.0567)	(0.0925)
% Hispan * Year2001	-0.181**	0.0100	0.191*
	(0.0738)	(0.0620)	(0.107)
% Asian * Year2001	-0.467**	-0.00315	0.464**
	(0.212)	(0.0923)	(0.224)
Year2008	-0.0198*	0.00799	0.0278**
	(0.0116)	(0.00575)	(0.0112)
% Black * Year2008	0.0899*	-0.0324	-0.122**
	(0.0493)	(0.0243)	(0.0488)
% Hispan * Year2008	0.0275	-0.00135	-0.0289
	(0.0358)	(0.0169)	(0.0352)
% Asian * Year2008	0.0944	-0.0314	-0.126
	(0.0835)	(0.0313)	(0.0799)
Constant	-0.0134	0.833***	0.847***
	(0.298)	(0.227)	(0.286)
Basic Control	Y	Y	Y
State FE	Y	Y	Y

Observations	2,577	2,577	2,577
R-squared	0.149	0.558	0.298

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1