THE POLITICAL-ECONOMIC AND DEMOGRAPHIC CAUSES OF METROPOLITAN INCOME INEQUALITY AND ITS COMPONENTS

A Dissertation

by

XI CHEN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2009

Major Subject: Sociology

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Approved by:

Chair of Committee,	Mark Fossett
Committee Members,	Dudley Poston
	Rogelio Saenz
	William McIntosh
Head of Department,	Mark Fossett

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ABSTRACT

The Political-economic and Demographic Causes of Metropolitan Income Inequality and Its Components. (May 2009)

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Chair of Advisory Committee: Dr. Mark Fossett

This research project examines variations in inequality in individual earned incomes across U.S. metropolitan areas. The main analysis includes thirteen explanatory variables from three major perspectives – the political economy perspective, the demand-side perspective and the labor force supply-side perspective. In addition, I applied path models to explain causalities between some independent variables and used the decomposition of the Theil index to show the between-group effects. The results indicate that most demand-side and supply-side factors significantly contribute to variances in metropolitan income inequalities, while the impact of political economic factors are very limited.

The paper is organized in the following manner: Chapter I is the introduction; Chapter II reviews literature focusing on the level of earning inequality and its predictors; Chapter III describes data and measures of variables; Chapter IV introduces statistical methods (including OLS regression model, path analysis, and decomposition of the Theil index); Chapter V presents the results of OLS regression model and its explanations; Chapter VI explains path analysis and decomposition analysis and their

results; and finally, Chapter VII discusses the current research project and its implications for future studies.

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CHAPTER I

INTRODUCTION

Inequality in income distribution is a topic of longstanding interest to sociologists and other social scientists. It has obvious importance in its implications for the distribution of social well-being and life chances. Accordingly, it has been the subject of study and theorizing by sociologists from many perspectives ranging from neo-Marxist class analysis (Wright 1979, Wright and Perrone 1977) to neo-Weberian analysis (Parkin, 1979; Weeden, 2002) and the status attainment perspective (Blau and Duncan, 1979, Sewell, Haller, and Ohlendorf 1970; Solon 1992).

Overview of Income Inequality

Income inequality is a crucial indicator of stratification, economic development, and many other aspects in society. At the individual level, differences in income can be a cause or a consequence of educational and occupational achievement (Hauser, Featherman 1974; Blau and Duncan 1979; Solon 1992), personal wealth (Shapiro, 2004), and even choice of residential location (Massey and Fischer 1999; Jargowsky 1996). At the societal level, income inequality is associated with industrialization (Kuznets 1955), gender inequality (McCall 2000a), immigration (Borjas 1982, 1985; Stolzenberg and Tienda 1997; Poston 1984), health conditions (Wilkinson and Pickett 2006, Kawachi etc. 1997), as well as class and racial inequality (Wright 1978, Wright

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and Perrone 1977, Wilson 1997), and family structure (Treas and Walther 1978).

Recent Trends and Patterns in Income Inequality

Income inequality is viewed as an important subject because of its dynamic nature across time and space. In the U.S., the trend in income inequality since World War II can be divided into two distinct time periods (Ryscavage, 1999). During the first period (1947-1973), overall income distribution was relatively consistent, with inequality slightly rising during economic downturns and slightly declining during economic expansions (Ryscavage, 1999). However, inequality in both family and individual income began to increase rapidly in the late 1970s. The U.S. Census Bureau's Current Population Survey (CPS) data shows that the Gini index for family income inequality was fairly stable, around 0.37 from 1947 to 1973, but increased from .356 to .425 between 1973 and 1996 (Ryscavage, 1999). Individual income inequality also rose over 20% from 1965 to 2005 according to the Gini index (see Figure 1.1).

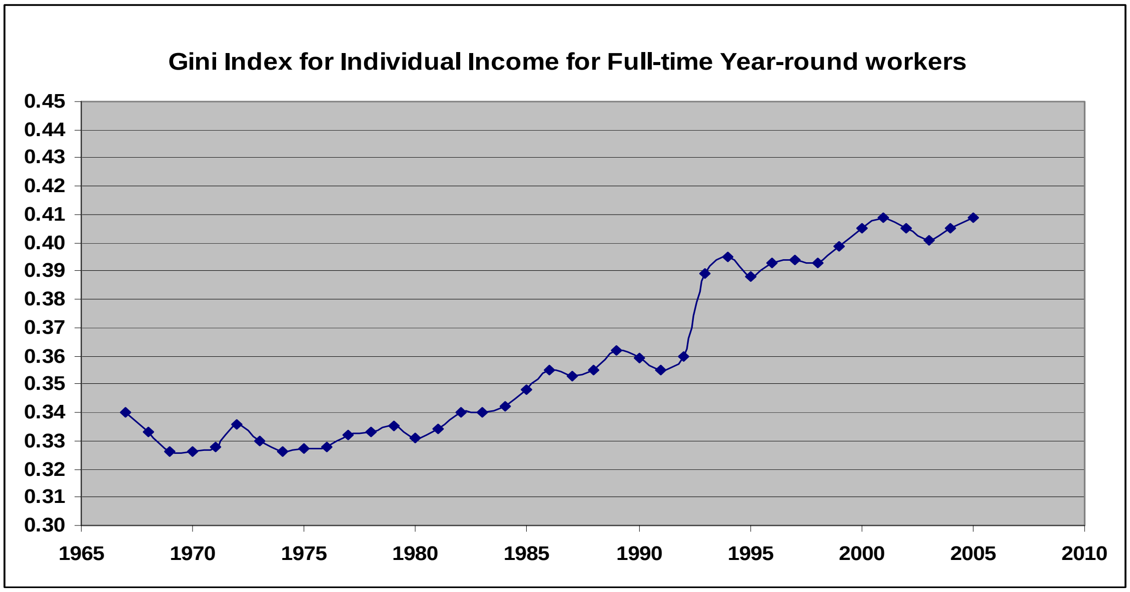


Figure 1.1 Trend for U.S. Individual Income Inequality

Many researchers and theorists have viewed these trends and patterns with concern. Douglas Massey (1996), in the article “The Age of Extremes,” has warned that rising income inequality contributes to geographic concentration of affluence and poverty in urban areas. The spatial concentration of affluence reinforces the privilege and power of the rich, while as the density of poverty increases, the poor face more crime, disease, and family dysfunction, therefore “creating a deeply divided and increasingly violent social world” (Massey 1996, P.395). Furthermore, compounded with urbanization and natural population growth, income inequality escalates even faster in some developing countries such as Mexico, China, and India (Massey 1996, Firebaugh 2003).

In the U.S., as the dominant industrial form shifts from manufacturing to service, the labor market appreciates “soft skills” more than physical strength (Levy, 1998). As a result, inequality continues to increase due to the growing economic premium on education and skills and “a winner-take-all market in which the very highest incomes grow enormously while all other income stagnates” (Levy 1998, P.77). Furthermore, unemployment in inner city ghettos has reached record levels, exacerbating social inequality and its subsequent negative consequences, threatening the fabric of American society (Wilson, 1996).

Income distribution also varies greatly across geographic locations. For example, at the global level, national income inequality grew in all regions except for Africa. Specifically, income inequality doubled in Eastern Europe over the last four decades and from 1980 to 1995 it rose over 20% in some Asian countries (Firebaugh, 2003). In the U.S., income inequality also varies from state to state. For instance, in 1990, the Gini index of family income in New Hampshire was 0.387, while it was relatively high at 0.475 in Mississippi (Volscho, 2005). Across U.S. counties inequality varies because of counties’ considerable differences in economic infrastructure, demographic profile, and level of prosperity (Nielsen and Alderson, 1997). Between the 1960s and the early 1980s, a number of cross-sectional studies have examined income inequality across states (Aigner & Heins 1967; Al-Samarrie &Miller 1967; Conlish 1967; Formby and Seaks 1978; Hylack 1980; Jacobs 1985; Singh & Sale 1978, Langer 1999) and across U.S. metropolitan areas (Betz 1972; Burn 1975; Danziger 1976; Farbman 1975; Garofalo & Fogarty 1979; Hirsch 1982; Maume 1983; Nord 1980; Sakamoto 1988). According to information from Metropolitan Quality of Life Data at Harvard University, the Gini index of income inequality in the largest 100 U.S. metropolitan areas in 1999 ranged from 0.48 for New York City to 0.37 for Nassau-Suffolk area (See figure 1.2). Such a large variance in inequality across metro areas brings up pertinent questions as to why these inequalities exist, and why a variance in the inequalities exists. This is in part what the current project is attempting to answer.

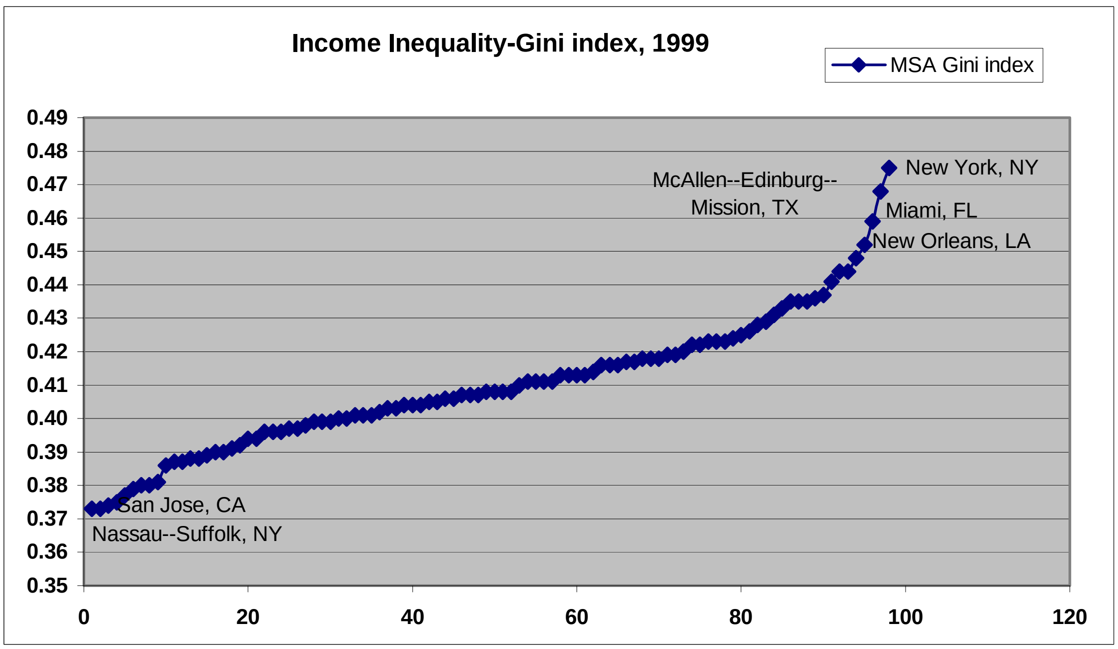


Figure 1.2 U.S. Metropolitan Income Inequality for the Year 1999

Surprisingly, neither the recent increase nor the spatial variance of income inequality has received much attention from sociologists in the last decade. To shed new light on the subject, the goal of this study is to understand various forces and factors that shape income distribution across metropolitan areas and evaluate their relative importance from a sociological and economic point of view.

Causes for Income Inequality

Sociologists and economists have examined the potential causes of income distribution for several decades. Most studies can be grouped into three broad perspectives. The first perspective emphasizes political-economic factors, such as public policy, federal or state laws, interest groups, class conflict, and workers' organizations. Concerning income inequality in particular, union density (Beck 1980, Rubin 1988, Leicht 1989, Freeman, 1997, Gustafsson and Johansson 1999), right-to-work laws (Moore and Newman 1985, Ellwoood and Fine 1987, Abraham and Voos 2000), the minimum wage (Danziger and Gottschalk 1995, Freeman 1996, Diego and Wodon 2004, Volscho 2005), and public education system (Glomm and Ravikumar 1992, Wilson 1996) are among the most frequently mentioned variables.

The second and third perspectives are derived from fundamental ideas in economics – the demand and supply sides of the labor force. Demand-side theories emphasize the structural opportunities of jobs and particularly examine factors such as industrial and occupational structure (Kuzent, 1955, Freeman 1977, Levy 1998, Wilson 1996, 1997, Bluestone 1990, Gustafsson and Johansson 1999), size of the public sector (Gustafsson and Johansson 1999, Hinrichs and Lyson 1995, Volscho and Fullerton 2005), unequal treatment of racial groups (Gwartney and Long, 1978, D'Amico and Maxwell 1995, Darity, etc. 1997, Darity and Mason 1998, , Hamilton 2000, Coleman 2003) and structural and cyclical unemployment (Gustafsson and Johansson 1999, Nielsen and Alderson 1997) on job availability and differences in wages.

In contrast, the supply-side argument claims that inequality is produced by the distribution of characteristics across individuals in the labor force. For example, it is argued that heterogeneity in talent, motivation, and human capital (Thompson 1965, Burn 1975, Freeman 1997, Mincer 1974, Sullivan, 2006), immigration (Stolzenberg and Tienda 1997, Reed 2001, Chiswich 1978, 1986, Bojas 1982), and age and racial composition (Bollen and Jackman 1985, Nielsen and Alderson 1995, 1997) generate variation in income compared to a homogenous population in the above categories. In addition, the non-linear effect of demographic characteristics on income inequality has been explained by the logic of Kuznet's curve (Nielsen, 1994). That is, for two groups that differ in income, inequality is greatest when they are equal in size and lower when one of the two groups predominates.

While individual studies examine relevance of particular factors, most studies do not consider all factors together, or quantitatively compare their importance in affecting inequality, nor suggest the most compelling argument among them. What is missing is a broad picture that includes all major theories and hypotheses and an empirical test of their relative strength. Therefore, this study sets out to accomplish this goal by addressing inequality in income across U.S. metropolitan areas with U.S. census data.

Measure of Income Inequality

To determine income inequality one needs define income first, because the calculation of inequality can be very sensitive to how income is measured (Ryscavage 1999). The value of income inequality could be higher if the definition of income includes salary, wage, dividends, retirement pension, interests received from investment such as stock, and nonmonetary transactions such as health insurance, Medicare and Medicaid, which are over-proportionately received by the rich. Conversely, the value of income inequality could be lower if certain redistributive transfers such as welfare payment, public assistant, Supplemental-Security income, veterans' payments, unemployment compensation, subsidized housing, and food stamps are included in incomes of the poor (Ryscavage 1999). Most empirical studies that investigate inequality use either individual earnings or relative loosely defined monetary income as the measure of income, depending on researchers' interest. Earnings from work such as wages and salaries generally constitute the largest part of income. With respect to factors of production, earnings are viewed as the return to labor (Ryscavage 1999). Since this study focuses on inequality generated through labor market structure and dynamics, the concept of income used here refers to labor market earnings, or earned incomes.

In measuring income inequality, this study uses the Theil index. Of the five popular inequality indexes (squared coefficient of variation, Gini index, Theil index, mean logarithmic deviation, and variance of logged income), only the Theil and mean logarithmic deviation satisfy the criteria of scale invariance, additive decomposability, principle of transfers, and welfare principle (Firebaugh 2003, P. 80). The additive decomposition of Theil inequality measure is used, where appropriate, because of its property of separating out within-group and between-group components. The comparison of weighted and unweighted between-group components can also help demonstrate how population distribution influences the values of inequality.

Another contribution of this study is to seek the factors that could influence the decomposed between-group component of inequality measures. Prior research has compared multiple popular inequality measures, such as the Gini index (Nielsen, 1994), the Variance of Logged Earnings (Sakamoto, 1988), or the Atkinson index (Volscho and Fullerton, 2005), but paid less attention to the *components* of inequality. According to Duncan (1966), the decomposition of dependent variables makes it possible to "compute the relative contribution of components to variation in the composite variable and to ascertain how causes affecting the composite variables are transmitted via the respective components" (Duncan 1966, P.7).

Future Implications

Income inequality has risen in the most populous nations, such as China, India, the former USSR, and the U.S. The growth in inequality in developing countries can be viewed as a result of their economic liberalization, while causes of inequality growth in the U.S. and Western European countries are more complicated (Firebaugh, 2000, Levy and Murnane 1992). However, most nations do not document data as sufficiently and accurately as the US Census does, thus creating barriers to investigating growing inequality in other nations. In this study, the knowledge obtained by examining an integrative conceptual framework and applying advanced techniques will be instructive in future investigation that seek to explain income inequality in other countries. Furthermore, as urbanization processes speed-up rapidly all over the world, the present study focusing on U.S. metropolitan areas in particular also could help forecast the dynamics in inequality in urban settings at the global scale, as well.

CHAPTER II

PREVIOUS RESEARCH AND HYPOTHESES

This chapter reviews the existing literature on income inequality with three goals in mind. One is to document the level, geographic variation, and trend in income inequality established by previous research. The second is to identify factors that are considered to be important in explaining the level and variations in income inequality within previous literature. The third is to develop the current study's hypotheses to be tested in this study.

Patterns and Trends

Several scholars have provided a thorough review of historical trends in inequality in earned income in the post-war period in the U.S. Levy and Murnane (1992) briefly reviewed U.S. male earnings inequality during the last 150 years[1], and documented detailed changes in three consequential periods: 1970-82, 1983-87, and the post-1987 period. The first period (1970-82) was marked with stable inequality but falling experience and education premium due to the entrance of baby-boom cohorts into the labor force (Levy and Murnane 1992). The second period (1983-87) was the period of declining middle-class jobs and polarization between the rich and the poor. The particular political and economic environment during the early 1980s – tax rate reductions for the top brackets due to the Economic Recovery and Taxation Act in 1981

[1]The description of male earning inequality during the period between the Civil War and the early 1950s is reviewed in Levy and Murnane's work.

and a high unemployment rate during the economic downturn, contributed to the continuing increase in inequality. As academic interests on the subject resurged, different theoretical arguments started focusing on the demand-side factors. Perhaps the most influential work among them was Bluestone and Harrison's deindustrialization theory (1982). But the fact that vanishing of middle class jobs and rising inequality occurred within both manufacturing and service industries suggests that the argument based on sectoral shift cannot fully explain rising inequality (Levy and Murnane, 1992). During the last period (1988-1991), earning inequality among males kept growing, despite a recovery in the economy and a decline in the effect of baby-boomers (Levy and Murnane 1992). Freeman (1976) suggested the post-1979 rise in education premium as an explanation, but it still cannot explain growing inequality among workers with similar schooling and experience, and in the same age groups (Levy and Murnane 1992).

Ryscavage (1999) divided the trend in earning inequality since post- WWII into two periods: 1947-1973 and 1973-1996. He described that inequality in the first period was relatively consistent, slightly increasing or declining according to economic growth and recession, respectively. Ryscavage's (1999) work gave more attention to the inequality trends during the second period, especially the differences in earning inequality between males and females. The general conclusion is:

> Over the 1970s and 1980s the amount of dispersion in the earnings distribution had increased, especially for men. For women, earnings inequality appeared to be on a gradual decline in the 1960s and 1970s, but then began to increase during the 1980s (Ryscavage, 1999 Pp101).

On the topic of between and within-group inequality across education and age groups, the gap in earnings between the more-educated and less-educated men was larger in the 1980s than in the 1970s (Levy and Murnane 1992; Ryscavage, 1999). Among male workers who had a high-school diploma, earnings of older workers relative to younger workers were changing more favorably over the 1971-89 period. Among college-educated workers, the earning differential related with experience rose during the 1970s but stagnated in the 1980s. During the 1990s, the forces that generated greater earning inequality were still present. While the early 1990s was a period of stabilization in income inequality, the Gini index of income inequality for year-round full-time individual workers rose sharply between 1993 and 1995 according to U.S. Census data.

Income inequality also varies across geographic locations. Between the 1960s and the early 1980s, a number of cross-sectional studies have examined income inequality across states in the U.S. (Aigner & Heins 1967; Al-Samarrie &Miller 1967; Conlish 1967; Formby and Seaks 1978; Hylack 1980; Jacobs 1985; Singh & Sale 1978). Langer (1999) examined the Gini index of household income inequality across states based on both Census and CPS data from 1949 to 1989. Louisiana had the highest level of income inequality (0.472) while New Hampshire had the lowest level (0.381) in 1989. Over time, different patterns in the level of income inequality emerged. Some states, including New York, California, Louisiana, and Delaware, had a steady increase in income inequality. Other states showed a cyclical change in income inequality, such as Nebraska and Virginia (Langer, 1999). Importantly, the variation across states and over time observed in the Gini index was found significant and not caused by sampling error (Langer, 1999).

Other cross-sectional studies have examined inequality across metropolitan areas. During the late 1970s and early 1980s, some researchers found a positive relationship between city size and income inequality level (Hirsch 1982; Maume 1983; Nord 1980; Garofalo & Fogarty 1979; Betz 1972). The emphasis in more recent literature has shifted toward explaining income inequality between- or within- population groups and the causes in socioeconomic infrastructure. For example, McCall (2000a, 2000b) analyzed the widened within-group inequality across gender and education categories in counties with a population over 100,000. The relevance of metropolitan racial composition to income inequality has become a popular research topic as well (Chakravorty 1996; Cohen 1998, 2001; McCall 2000b). In addition, more scholars have started paying attention to the impact of industrial sectors and economic infrastructure on income distribution (Bluestone 1990; Neilson and Lorence 1988; Sakamoto 1988; Belman etc. 1996; Volscho and Fullerton 2005; Lorence 1991; Sanchez 2002).

Causes of the Variation in Inequality

This section reviews research findings on three major perspectives on income inequality. First, based on the political economic perspective, I examine the impact of unionization, Right-to-work laws, minimum wage, and public education on income inequality. Then, incorporating the demand and supply paradigm in economics, I group the possible causes of income inequality into the demand-side perspective and supply-side perspective. The demand-side factors include industrial structure, occupational structure, size of the public sector, racial inequality, and unemployment rate. The supply-side factors include the distribution of human capital, the size of immigrant population, ethnic composition and age structure of the labor force.

Political Economic Variables

The political economic perspective emphasizes social structural factors related with public policy, federal and state regulations, and political and economic conflicts between interest groups. The following factors have been suggested as potential influences on income inequality: unionization, right-to-work (RTW) laws, the minimum wage, and the public education system.

Unionization

Unionization has been considered as an equalizing factor for income inequality. For example, the percentage of unionized workers in industrialized countries is negatively associated with the income inequality measure (Gustafsson and Johansson, 1999). Furthermore, the decline of trade unions in the most advanced industrial countries has contributed to increases in inequality (Freeman, 1997). Unions not only reduce inequality in income among union members by standardizing pay among them within industrial units, e.g. plant, factory, or firm, but also equalize pay across units and reduce inequality by narrowing the earning gap between blue collar workers and highly paid professionals and executives. Furthermore, unions can generate a threat effect that force nonunion firms to increase pay and benefits to avoid unionization (Leicht, 1989).

In the U.S., the decline in unionism from 30% in the private sector in the 1960s to 10% in 1996 has been a contributing factor in the rise in income inequality during this period (Freeman 1997). The possible causes for the decline in unionization include lower union response to the changing labor market environment (e.g. globalization and immigrantion), and a change in employer attitudes toward unionization. Most factories or firms treated unions as a crucial element of the American labor system before the 1970s, but after the 1970s the employers' attitude became more averse to unionism (Freeman, 1997). Free trade and subsequent large volumes of imported goods from foreign countries have substantively weakened the bargaining power of union workers in good-producing industries. Furthermore, excess supply in labor due to more immigrants has created a long-lasting replaceable labor source for firm owners and therefore made union's effectiveness and influence fade. The empirical analysis on union effectiveness is extensive among literature in political science, especially on union's interaction with class, race, and gender.

Union and Education/Class

While few studies have examined the association between unionization and income inequality among workers with differing education, some findings have suggested that unions serve as a divisive function among different classes (Rubin, 1988). For example, union density is positively associated with the redistribution of earned income from middle-class workers to both the most prosperous (the fifth quintile) and least prosperous (the lowest quintile) workers (Rubin, 1988). For the most prosperous workers, “highly institutionalized unions with a highly skilled membership are able to extract greater economic gains from their employers than other unions or nonunionized labor” (Rubin 1988, P.563). For the less-skilled workers, unions may increase income inequality between unionized and nonunionized members (Form, 1985). However, the union threat effect can also raise the earnings of unorganized workers, and therefore reduce the inequality among unskilled workers (Leicht, 1989). Thus, unionization could have different impacts on between-group inequality than compared to within-group inequality.

Unions and Racial Inequality

Beck (1980) listed two perspectives on unionization and racial inequality. The first perspective argues that unions function as a tool of a white working class to protect their social status and economic power by excluding racial minorities from its membership. Therefore, increasing unionization will hypothetically widen income inequality between white and non-white workers, while reducing inequality among white workers. The second perspective suggests that since unions provide solidarity and economic gain to both white and non-white workers, increases in unionization will reduce both between- and within-race inequalities. The results of time series data from 1947-74 suggest that decline in unionization reduces white-nonwhite income inequality, while increases in unionization reduce inequality among white workers but increase the inequality among nonwhite workers (Beck, 1980).

Unionism and Gender

Narrowing gender gap in unionization has reduced 7 percent in the wage inequality between males and females in Canada during 1981-1988 and one-seventh of the total decline in gender wage gap in the private sector in the U.S. during 1973-1988 (Doiron and Riddell 1994). While in Canada narrowing of gender unionization was due to increasing female union members, in the U. S. narrowing gender unionization was caused by a faster decline in male union members than female union members. Thus, changes in union density could have different effects on male and female income inequality.

Although unionization may influence total income inequality in many different ways, the general idea revealed by the above studies is that the union reduces the income gaps between workers. In this study in particular, I will test the hypothesis (H1) that the degree of unionization has a negative impact on income inequality in U.S. MSAs.

Right-to-work (RTW) Law

A right-to-work law is a state law that bans union security. As a government regulation, RTW laws have both direct and indirect effects on income inequality. While no direct impact of RTW laws have been tested with data, studies suggest that states with lower wages are more likely to pass an RTW law (Moore and Newman 1985). Passing a RTW law in Louisiana and Idaho has significantly increased the state's shareholders' wealth by 2-4% (Abraham and Voos 2000), but no significant increase in income of working- class workers has been mentioned. If RTW laws uphold the number of workers who work at low wages and provide higher returns to the rich, metropolitan areas located in the states that have RTW law could have higher income inequality than those without such laws. Thus I hypothesize (H2) that passing RTW laws increases overall income inequality.

Studies also show that passing RTW laws is relevant to unionization. On the one hand, RTW laws have negative effect on the extent of unionization. On the other hand, the extent of unionization in a state also has a significant negative effect on the probability of a state passing RTW laws (Moore and Newman, 1985). Studies treating a RTW variable as exogenous found that RTW laws have a significant negative effect on state unionism (Moore and Newman, 1985). Regardless of the debate on the causal effect of RTW laws on unionization, most studies found that passing RTW laws and reduction in unions go hand in hand (Ellwoood and Fine 1987, Moore Newman 1985). It seems that both unionization and RTW law are the factors that influence the possibility of workers to bargain with employers, although unions may have a larger impact on workers' income than RTW laws and therefore exert more influence on income distribution.

Minimum Wage

The minimum wage can potentially influence income inequality as well. According to Danziger and Gottschalk (1995), the minimum wage was fixed in nominal terms at $3.35 per hour between 1981 and April 1990. However, its real value declined by 44% during this period due to rising inflation. Since the average wage also increased modestly, the real minimum wage fell from 46% of the average wage in 1981 to 35% in 1989 (Danziger and Gottschalk, 1995). Thus, while the nominal value of minimum wage had increased, its real value in the early 1990s was well below that of the 1970s (Danziger and Gottschalk, 1995, p.129). As a result, this decline in minimum wage has been partially responsible for the increased earning inequality during the 1980s and a crucial factor for declined earning among young people, immigrants, and those with low education. While the minimum wage could explain the increased income gap between population groups, it has limited influence on income inequality among prime-age college graduates (Danziger and Gottschalk 1995).

Institutional economists also suggest that minimum wage serves to redistribute economic outcome and therefore reduces income inequality (Volscho, 2005). By setting a standard price, minimum wage increases the pay of the lowest-paid workers and limits the profits for others (Freeman, 1996). Since the consumers of the products of minimum wage workers and stakeholders are potential payers for the increasing minimum wage, "the higher the level of the minimum wage, the greater are the potential redistributive benefits" (Freeman, 1996, P. 648).

Although a higher minimum wage appears to have some have at least some inequality-reducing effect, its net impact is influenced by the share of low-skilled workers (Diego and Wodon 2004). For example, the impact of changes in minimum wage is relatively small in a country such as the U.S., where only a small proportion of workers are affected, than compared to a developing country with a large share of workers earning a minimum wage (Diego and Wodon, 2004). In the U.S., states set their own minimum wages. From this perspective, it would follow that states with a higher minimum wage will have lower income inequality (H3).

Public Education System

Public education systems can reduce the inequality by providing equal quality of education for all students regardless of the social standings of their parents. Glomm and Ravikumar (1992) compared two regimes of public schools and private schools and found that "income inequality declines faster under public education than under private education." Although research on public education and income distribution is limited, William Julius Wilson has repeatedly emphasized the importance of the quality of public schools on educational experiences of children who grow up in poor neighborhoods (Wilson 1996, 1997). Wilson's goal is to promote policy reform, but it suggests that uneven public education across neighborhoods and cities would influence income distribution by creating different proportions of highly-educated, less-educated, and non-educated populations.

Demand-side Variables

The demand-side theories claim that income inequality reflects the distribution of structural opportunities that the market can offer to the labor force. In other words, demand-side factors are those that affect how many jobs are available in various industrial and occupational categories. The most widely discussed demand-side factors in studies on income inequality include industrial and occupational structure, size of the public sector, racial inequality caused by discrimination, and unemployment rate.

Industrial Restructuring

As a driving force of industrial restructuring, deindustrialization process influences the distribution of workers across all industries, which in turn affects income distribution among workers. For instance, both increasing job opportunities in finance, investment, real estate (FIRE) and technology-oriented industries and declining job opportunities in manufacturing industries has widened the income gap between white-collar workers and their employers and between professionals and craft workers. A study focusing on 16 countries has shown a significant relationship between the level of inequality and the sector composition of the economy by pointing out that a decrease in the industrial sector fosters inequality while the large size of the public sector reduces income inequality (Gustafsson and Johansson, 1999).

The association between industrial development and inequality has formerly been described as an inverted-U shape of the Kuznets Curve. Kuznet's theory states that while an economy with a large low-paying agricultural sector and a small high-paying industrial sector produces relatively low inequality, inequality gradually increases as the population flows from agricultural to industrial sector, then peaks, and finally decreases as industrial jobs dominate the labor force (Kuzent, 1955). Cross-national analysis has provided empirical support for this hypothesis. However, since the 1970s, industrialized countries such as the U.S. and the U.K., have moved beyond the prediction of Kuznets' curve and entered a new inequality-climbing phase. This inequality growth in the post-industrial period has been labeled as Great U-turn by economists, which not only occurred in terms of variance in wage but also in real average wage, and among many demographic groups in all regions of these countries and different industrial sectors (Bluestone, 1990).

During the post-industrial period, as the market demand shifted from manufacturing goods to services, information, and technology, labor composition adjusted correspondingly. On the one hand, many middle-class jobs provided by manufacturing industries disappeared. On the other hand, the shift to the service sector created some high-paying and some low-paying jobs, which produced even greater wage dispersions. As a result, "there were fewer jobs for autoworkers and more jobs for hamburger flippers", and such redistribution of the labor force influenced overall inequality even if the wages paid within each industry remained unchanged (Danziger and Gottschalk, 1995).

Another important theory, the dual-economy theory, examines the influence of industrial structure on the nature of work, how much a job pays, and job security. According to this theory, all firms are divided into two networks: the "core" and the "periphery" (Hodson and Kaufman 1982). Firms belonging to the "core" are usually large in size, corporate and bureaucratic, highly integrated through ownership and serve broad markets (Averitts 1968, p.7). Jobs provided by such firms are generally contractual, stable, and highly paid (Sullivan, 2005). Conversely, firms in the “periphery” are relatively smaller, self-employed, and operate in restricted markets (Averitts, 1968). Accordingly, such firms provide short-period, unstable, and low-paying jobs (Sullivan, 2005). The impenetrable labor market barriers between the core and the periphery blocks upward mobility of workers moving between job positions and therefore sustains the stratified economic structure and income distribution among workers.

Rising global economy and international competition constitute another cause of structural shift in the post-industrial society (Danziger and Gottschalk, 1995). International trade, especially with less developed countries (LDC), could contribute to problems of unemployment and increasing low-wage workers within more developed countries (MDC) and therefore lead to higher income inequality within MDC (Freeman, 1977).

Information technology as an emerging industry during the 1990s in the U.S. also could influence inequality in income. The NASDAQ composite index, heavily influenced by high-tech stocks, rose from 776.80 to 4,696.69, an over 600% increase, between January 1994 to February 2000 (Galbraith and Hale 2003). As high-tech firms gain more profit, their employees may receive higher wages than those in other industries. During the information technology bubble (1994-2000), the U.S. cross-county income inequality increased 48%, the largest inequality growth since 1969 (Galbraith and Hale 2003). Uneven distribution of technology industry across geographic locations has contributed to between-county differences. Comparing inequality levels between 1994 and 2000, “the big gains occur around areas of the county known to have a high-tech emphasis (e.g. Sicilon Valley, Seattle, and Boston), while losses occur in rust belt counties (Flint MI, Clevland OH) and counties heavily reliant on tourism (Honolulu)" (Galbraith and Hale 2003, P.9). Above theories point out that industrial restructuring that happened in post-industrial period lead to increases in income inequality. In other words, the process of deindustrialization seems to increase inequality (H5).

Occupational Structure

Similar to industrial restructuring arguments, theories related with occupational structure also emphasizes the impact of macroeconomic change on the labor demand. While the shift occurred between manufacturing and service industries can influence the distribution of jobs, what types of jobs are provided within an industry is a separate question. Advances in technology requires more technical training, skills and education in workers of certain occupations, regardless of the nature of the industry. For example, the earnings in the service sector range from the minimum wage in fast food restaurants to extremely high pay for others such as physicians (Levy 1998, P.60). Furthermore, occupational structure also involves supply-side factors. The growth in college graduates and technically skilled workers has not kept up with the market demand for such workers, which in turn leads to higher premium for education and skills. Thus, the interplay of demand- and supply-side factors generates a polarized occupational structure and unevenly-paid jobs.

Levy (1998, P.14) specified five groups of occupations that are directly associated with individual earnings. They are high-skilled and highly-paid workers (e.g.

mangers, administrators, scientists), other white-collar workers (e.g. sales clerks, officers), high-skilled blue-collar workers (e.g. craftsman, machines and equipment operators), low-skilled service workers (e.g. cooks, custodians, barbers), and farmers and workers in farm-related occupations. Such detailed typology more accurately demonstrates the stratification of jobs than the simple division of the "core" versus the "periphery," or manufacturing versus service proposed by theories focusing on industrial restructuring. It has been documented that the earning distribution of a particular race and sex group is closely related to the types of jobs that the group predominately holds in the occupational structure (Levy, 1998).

A more detailed occupational classification is suggested by the hourglass economy argument, that emphasizes abundance of jobs at the top and bottom of the occupational distribution but few jobs in the middle. Estimating hourly wages by the most detailed occupational categories available in each of the three censuses (1950, 1970, and 1990), Massey and Hirst (1999) generated over 200 "occupational wages." Over this period, the changes in the shape of the distribution of occupational wages among men corroborate the hourglass metaphor, but it does not apply to the distribution among women (Massey and Hirst 1998). Therefore, I hypothesize that the more stratified occupational structure generates higher income inequality in metropolitan areas (H6).

Public Sector Employers

In addition to the changes in industrial and occupational structure, labor economists and industrial sociologists also emphasize the importance of public sector employment on income distribution (Hinrichs and Lyson, 1995).

Increasing jobs from government employers could reduce income inequality for several reasons (Volscho and Fullerton 2005). First, government employers not only can set a ceiling on the wage of workers at higher levels, but also pay more than private-sector employers for low-skilled workers (Volscho and Fullerton 2005). Second, government employers are more likely to hire women and minorities than private-sector employers (Volscho and Fullerton 2005; Peters 1985). Additionally, once hired, women and minorities face less wage discrimination for working for government employers than working for private-sector employers. Therefore, the share of workers in government sector in MSA labor force could potentially influence income distribution among workers. Using three measures of the proportions of government sector workers, Volscho and Fullerton (2005) found that the size of the public sector negatively correlates with the income inequality in metropolitan areas. In this analysis, I will retest this hypothesis, namely, the more jobs in the public sector, the lower income inequality of a MSA (H7).

Racial Inequality

Another possible demand-side factor is racial income inequality that partially caused by discrimination in the labor market. Structural or individual discrimination potentially reduces the earned income relative to whites for the disadvantaged groups who have similar education, experience, and job performance. However, whether currently racial inequality in the U.S. is caused by discrimination has been debated among both sociologists and economists. On the one hand, scholars have collected data from content analysis, court cases, audit studies, and used the residual method and Blinder-Daxaca decomposition as evidence of the impact of discrimination on individual economic outcomes (Darity, Mason 1998). On the other hand, some economists argue that pre-market factors play a more important role in explaining the racial income gap (Heckman 1998, Neal and Johnson 1996). Using the Armed Forces Qualifying Test (AFQT) score measured among high school students, Neal and Johnson (1996) show that the majority wage differential between blacks and whites can be predicted by AFQT scores measured before the respondents entered the labor market, but critics argue that the AFQT itself is racially biased. Some economists also argue that the explained difference used in the residual method is not equal to discrimination but, instead, are equal to the human capital variables that are not included in the model (Follett, etc, 1993).

Another group of scholars suggest that the impact from both individual characteristics and employment discrimination coexist. Gwartney (1978) examined the relative earnings of eight racial and ethnic minority populations living in U.S. urban areas during the 1960s and 1970s, and found that while the earnings ratio between minorities and whites increased during this period, the magnitudes and source varied considerably. For instance, the large improvement in relative earnings of Japanese, Filipinos, and Chinese was due to their improved personal characteristics and endowments, but the relative earning gain among Blacks and Puerto Ricans was a result of reduction in racial differences in both human capital and discrimination (Gwarteny, 1978). Since it is difficult to measure the inequality caused by racial discrimination, I simply use a measure of income inequality between black and white, which can be produced by labor market discrimination, but also can be influenced by other factors that cannot be attributed to labor market discrimination. I expect the racial income inequality will have positive effect on the metropolitan total income inequality (H8).

Unemployment

Macroeconomic fluctuations can also affect income distribution. "Unemployment is more likely to hit those at the bottom of the income distribution harder than others, therefore unemployment has an inequality-generating effect" (Gustafsson and Johansson, 1999, page 587). However, in their own research, Gustafsson and Johansson (1999) found no association between the unemployment rate and inequality. The weak relationship between the two could occur because income losses from unemployment are masked by unemployment benefits or by increases in labor market- orientated activity by other family members (Gustafsson and Johansson, 1999).

Yet, other studies treat unemployment as a consequence of deindustrialization and globalization and international competition (Nielsen and Alderson, 1997). According to this argument, high unemployment caused by global forces will lead to high income dispersion in developed countries, but Nielsen and Alderson (1997) found that a ambiguous effect of unemployment on and income inequality at the county level in the U.S. from 1970 to 1990. As Gustafsson and Johansson (1999) suggested, other macro level processes, such as receipt of unemployment benefits, may have counterbalance effects. Mocan (1999) also suggests that changes in structural (long-term) unemployment has more significant influence on income inequality than changes in cyclical (short-term) unemployment[2]. Although previous literature didn't find a significant association between unemployment and inequality, their theoretical propositions suggest there is a positive relationship. Therefore, I expect that increases in unemployment rate leads to higher income inequality (H9).

Supply-side Variables

The supply-side theories argue that income inequality reflects the unevenly distributed social characteristics, e.g. education, skills, and training among workers. Economic equality in a population is produced when the labor force is a homogenous group based on the above social characteristics. The most frequently discussed supply-side factors that influence the level of income inequality include the distribution of human capital, the size of immigrant population, and population's racial and age structures.

[2] "An increase in structural unemployment is associated with an increase in the income share of the richest twenty percent of the population, and with a decrease in the shares of the bottom three quintiles… An increase in cyclical unemployment is associated with a reduction in the income share of the second quintile." (Mocan, 1999, p128).

Human Capital

Educational achievement, working experience, level of training and skills are often referred to as the indicators of human capital. The productivity of labor among individual workers is closely related to their human capital resources (Becker, 1975). Economic theory proposes that each individual intends to maximize his/her economic welfare and thus invest in their human capital stock. As a result, the difference in the returns to such individual investment reflects income differentials (Burn, 1975). The greater the variance in education, vocational training, talent and skill is in the population, the higher the income inequality (Thompson, 1965).

Previous research has suggested a link between variance in education and income inequality. According to Jan Tinbergen, a Nobel Prize-winning Dutch economist, inequality is generated by the race between the increasing demand for highly educated workers due to technology advancement and the increasing supply of these workers because of diffusion of higher education. The history of industrialized countries has shown that these two forces were compatible most of the time because the increase in the supply of skills often balanced the increase in the demand for skills (Freeman, 1997). During the 1970s, the increase in supply outgrew the increase in the demand for skills and therefore reduced educational premiums. However, during the 1980s, the rate of students graduating from college decelerated and this led to increases in the wage return for the more educated (Freeman, 1997). Thus, the slowdown in the growth of the supply of more educated workers relative to less educated workers is one of the factors that contributed to the increase in income inequality (Freeman, 1997).

Work experience represents the second major source of human capital, and is often measured by the number of years a person has worked in the labor market (Sakamoto, 1988). Workers' productivity and earnings are enhanced by their additional experience and training. Therefore, the gap in "working years" between new workers and senior workers, controlling other factors, would generate wage differences.

Early human capital views suggested that individual data can generate aggregate-level relationships – greater difference in human capital leads to greater earning inequality (Becker and Chiswick 1966, Chiswick 1974). This method derived to Mincer's (1974) "Human capital earnings function" in which earning inequality was explained by the variance in educational attainment, the variance in experience, and variances in rates of return, and other covariance. Based on the above literature, I expect that larger variance in education among workers leads to higher income inequality in MSAs (H10).

Immigration

The increased racial diversity through immigration influences income distribution among individuals as well. While education is the most commonly used measure for human capital, language adequacy and racial/ethnic identity are conceptually part of the human capital framework (Sullivan, 2006). Recent immigrants carry very different human capital profiles than those of native-born whites in terms of education, language skills, social network, and other social and psychological assets.

Literature suggests that foreign-born populations can influence the wage structure in several ways. First, as more than one-third of the current foreign-born population do not have a high school diploma, they are more likely to bid down market wages for low-educated workers when competing with native-born whites with similar education for the same jobs (Reed, 2001). Second, low-paid minorities also bid up the wages of better-educated workers in certain industries that expanded with increases in populations, such as finance, investment, and real estate.

Furthermore, language deficiency among immigrants also influences their earning. Stolzenberg and Tienda (1997) compared the economic outcomes of both Hispanic and Asian immigrants based on their English proficiency and education and found that the immigrants' labor market disadvantage is determined by both their education and language. Immigrants with lower education and who do not speak English face the most severe discrimination and disadvantage (Stolzenberg and Tienda, 1977). The economic disadvantage of immigrants is so prevalent that it substantively influences a large share of the population at the bottom of the income distribution. In addition, increases in size and diversity of immigrant populations not only can increase the inequality between the native-born and immigrants but also influences inequality among non-white immigrants.

A large volume of work has focused on the current Latin American and Asian immigrants' labor market experience. Chiswich (1978, 1986) has documented the significant labor market disadvantage of Mexican immigrants and the decline of such disadvantage with an increase in the time of residence in the U.S.. As racial disadvantage declined further, the earning cross-over between foreign-born and native-born population occurred around 15 years after the immigrants entered the U.S.. However, Bojas (1982) suggests that diverse immigrant groups have showed different patterns of economic achievement. Particularly, immigrants from Cuba have gained higher schooling within the U.S. and are economically better off than the immigrants from Mexico and Puerto Rico. Bojas (1985) also pointed out that earning growth of immigrants over time is overestimated by cross-sectional data in Chiswich's study because the recent immigrants since 1950 have lower working-related "quality", such as education, than those of early immigrants. Still, literature has suggested the immigration increased income inequality during the late 1990s. Thus, I hypothesize that a MSA with a higher immigrant population has higher income inequality (H11).

Ethnic Demography

Just as the population size of immigrants varies across MSAs, racial composition also constitutes a unique labor force supply factor for each metropolitan area. Compared to non-white racial groups, whites in the U.S. have historically obtained more human capital resources, especially in education. Since the civil rights movement, the increased opportunities in education and occupation for the non-white population have improved the groups' socioeconomic standing. However, the social environment since the 1970s has not been able to completely remove the long lasting effect of racial discrimination and economic disadvantage for people of color. As a result, metropolitan areas that have heterogeneous racial groups could have higher earning inequality than those that have a more homogenous population. For instance, percent of black population is found to be positively related with the variance of logged earnings among workers of a metropolitan area (Sakamoto, 1988). In addition, more Hispanics and Asians entered the U.S since the 1970s, and "the foreign-born are more likely than the U.S.-born to live in metropolitan areas" (Kritz and Gurak, 2000, page 278). Therefore, I suspect that a MSA with racially diverse population has higher income inequality than a MSA with homogenous racial population (H12).

Age Structure

Because young adults and elderly people have relatively low income compared to middle-aged workers, the MSAs with larger proportions of young and elderly populations could have higher income inequality. Yet, little information could be obtained from previous studies at either the city or metropolitan level. Literature on cross-national comparisons indicates that the proportion of the national population under age 15 is positively correlated with income inequality (Bollen and Jackman, 1985).

In addition, the rate of natural growth in population is also positively associated with income inequality (Nielsen and Alderson, 1995, 1997), and such a relationship has been interpreted in terms of the impact of increases in population heterogeneity on dispersion of economic outcomes. Thus I expect that a larger age variance among workers leads to higher income inequality (H13).

CHAPTER III

DATA AND MEASURES

This chapter describes units of analysis, data collection and measures, and methods. First, I explain the units of analysis, sample size, and individual income data of the Census2000. Next, I compare the Theil index with other popular inequality measures in terms of their mathematical properties, and explain the decomposition function in detail. I then briefly describe the measure of each independent variable used in the analysis.

Unit of Analysis

Why do I choose metropolitan areas as the unit of analysis? Because, income inequality varies across metropolitan areas, and this provides a good opportunity to test different theories that intend to predict variance in inequality. Second, the Census2000 data shows that over 80% of the U.S. population lives in metropolitan areas, and we know from literature that many urbanites are non-white. The large size and diverse population makes it possible to consider the impact of demographical composition on inequality. Third, urbanization increases the concentration of poverty and the number of low-paying jobs, and meanwhile it creates groups of highly-paid professionals and the extremely rich. A large difference in income between groups of workers in U.S. metropolitan areas indicates its significance for an empirical study. Finally, we can find a clear definition from the U.S. Census for a Metropolitan Statistical Area - an area containing a recognized population nucleus with at least one urbanized area of 50,000 or more inhabitants and adjacent communities that have a high degree of integration with that nucleus. This makes the operationalization of variables and analysis more convenient.

There are 297 metropolitan areas from Census2000 included in the analysis. The inequality measures in MSAs, and some other independent variables are calculated from individual data of Census2000 5 percent sample, while other independent variables (i.e. unionization) are obtained from other census or surveys.

Individual Income Inequality

Since I am interested in inequality that is closely related with labor market characteristics (e.g. labor demand and supply and its demographic composition), and the earning of individual workers is largely determined by these characteristics in a particular market setting, I use individual earning data to calculate income inequality.

Although, literature on metropolitan inequality has used family income inequality, Sakamoto (1988) points out that family inequality has certain disadvantages in understanding the labor market mechanism, because family income inequality is not only determined by individual income within the family, but also by the number of family members, their age and demographic composition, household relationships among the family members, and financial resources other than income. However, individual income is able to reflect the influence of both demographic characteristics of an individual and political economic condition of a local market. Therefore, inequality measured at the individual level would provide more accurate information without bringing in the “noise” factor of family structure. The individual data in this study are obtained from the 5% Public Use Microdata Samples of US Census2000, and include all individuals residing in the 297 U.S. metropolitan statistical areas (MSAs), age equal to or over 16 years old, who are in the civilian labor force. There are 4,833,502 individual records used in the following analysis.

Measure of Dependent Variable

I use the Theil index to measure the dependent variable - income inequality. Before introducing this index, I will explain the properties of several common inequality measures. Measuring income inequality is more complicated than measuring income growth or gaps between units. Firebaugh (2003, page75) defines the standard inequality index as the measure of average disproportionality and can be expressed in the common form:

I (Inequality Index) = $\sum f(r_i)/N$,

Where N is the total number of cases, r_i ($r_i = X_j$/X-bar) is the income ratio for unit j, or the ratio of X for the jth unit to the average X for all units. Therefore, a measure of inequality is not only determined by the income ratio between individual and group means, but is also determined by the distribution of individuals among groups.

The most frequently used inequality measures in the social sciences are the Gini index, the Theil index, the Atkinson index, variance of logged incomes, and the mean logarithmic deviation. The criteria for evaluating these measures include the scale invariance, principle of transfers, the welfare principle, and additive decomposability. Firebaugh (2003, p79-80) provides a thorough review of each criteria. To satisfy *scale invariance* requires an inequality measure not being influenced by income change of the same rate for all individuals in the population. In other words, inequality does not depend on the scale used. The *principle of transfers* means that the value of the measure decreases when money is transferred from the rich to the poor, but increases when the same amount of money is transferred from the poor to the rich. The *welfare principle* states that income transfer among the poor is more significant than income transfer among the rich. The *additive decomposability* requires that the value of overall inequality is a sum of weighted within-group inequality and weighted between-group inequality, given that everyone in the population is classified into mutually exclusive groups. Additive decomposability is not important when the interest of research is to simply describe the between-group inequality, but it is crucial to studies that investigate the overall inequality and components that construct such inequality.

Of the five popular inequality indexes (squared coefficient of variation, Gini index, Theil index, mean logarithmic deviation, and variance of logged income), only the Theil and mean logarithmic deviation (MLD) satisfy all of the above criteria (Firebaugh, 2003, page 80). The Gini index satisfies the criteria of scale invariance and the principle of transfer but fails to obey the welfare principle and lacks decomposability. The variance of logged income does not satisfy the principle of transfer at the high income level, and the squared coefficient of variation does not satisfy the welfare principle (Firebaugh, 2003). While Atkinson's index satisfies the principle of transfers (Volscho and Fullerton 2005), it is not decomposable.

Moreover, these inequality measures capture the changes in income distribution differently because of their unique mathematical attributes (Ryscavage 1999). The coefficient of variation is more sensitive to relative income changes among high-income individuals than among low-income individuals and therefore "more sensitive to changes in the upper end of the income distribution" (Ryscavage 1999, p.38). The variance of the logged income is more sensitive to the changes at the bottom half of the distribution than to the upper half, while the Gini and the Theil index are more sensitive to changes occurring in the middle of the distribution (Jarvis and Jenkins 1998). Finally, the formula of the Atkinson index contains an "epsilon," a parameter that can be changed to adjust the sensitivity of the index by researchers. As the value of the epsilon increases, the index becomes more sensitive to changes taking place at the lower end of the distribution (Ryscavage 1999).

The rationale to use the Theil index is its advantage of meeting all criteria of inequality measure and its sensitivity to changes that occur at the middle of the distribution. This index was initially proposed by the econometrician Henri Theil (1967, p.102). Its property of additive decomposability is crucial for the analysis in that it separates out between-group and within-group differences, such as gender, race, occupation, etc. Furthermore, the components of inequality obtained through decomposition can be used as dependent variables to test different hypotheses. Duncan (1966) has suggested that decomposition of dependent variables makes it possible to "compute the relative contribution of components to variation in the composite variable and to ascertain how causes affecting the composite variables are transmitted via the respective components" (p.7). Finally, the "middle sensitive" attribute of the Theil index is beneficial for investigating the effects of a disappearing middle class, polarization of jobs in the service sector, and other causes suggested by both demand-side and supply-side theories.

Measures of Independent Variables

Variables Based on the Political Economic Perspective

Unionization (*Union coverage*) – *Union coverage* is measured by the percentage of workers covered by unions in a MSA. The data is obtained from Union Membership and Coverage Database which is compiled from the Current Population Survey (CPS) (Hirsch and Macpherson, 2003).

Right-to-work laws (*RTW law*) – information on state right-to-work laws is obtained from the U.S. Department of Labor (2006). The data is coded as a dummy variable, 1 indicating a state with RTWlaw in effect in 2000, while 0 indicates otherwise.

Minimum wage (*Minimum wage*) – Each MSA has been assigned the real value of state minimum wage in 2000. If the state law did not define a minimum wage, the MSA is assigned the 2000 federal minimum wage, $5.15. The information on state and federal minimum wage is also obtained from the U.S. Department of Labor (2007).

Public education system (public *education*) – Data and literature on public education system at the MSA level is limited. The Common Core of Data (CCD) of the

U.S. Department of Education provides total expenditure and total number of students in public elementary and secondary schools at the school district and MSA levels in 2000 (Johnson, 2004), and I calculated the average expenditure (in thousand dollars) per student to measure the quality of public education.

Variables Based on Demand-side Argument

Deindustrialization (*production industry*) – I use the percentage of workers in production industry from Census2000 data to measure the degree of deindustrialization. In other words, the higher the percentage, the less degree of deindustrialization in a MSA. According to the hypothesis that deindustrialization increases income inequality, I expect a negative sign for the coefficient of this variable.

Occupational structure (*occupational differentiation*) – The hypothesis states that a more stratified occupational structure leads to higher income inequality. To capture the *occupational differentiation*, I applied the first measurement mentioned in Gibbs and Poston's article (1975):

$$M=1-[\sum X^2/(\sum X)^2],$$

where X is the number of workers in any single occupational category. The advantage of this measure is that it reveals both structural and distributive differentiation (Gibbs and Poston, 1975). The higher value indicates more differentiated occupational structure. The data is also derived from the Census2000.

Public sector jobs (*public sector*) – The data is obtained from Union Membership and Coverage Database (Hirsch and Macpherson, 2003). The variable, *public sector*, is measured as the percentage of workers in the public sector among all workers in a MSA in the year 2000.

Racial inequality (*W/B income ratio*) – I use a simple white to black mean income ratio from the Census2000 data to measure racial inequality. Literature has suggested that the income difference among racial groups can reflect the long established social discrimination faced by minorities, especially for African Americans (Blau, and Ferber. 1987; Daymont, 1980).

Unemployment (*unemployment rate*) – This variable is measured by the percentage of workers who are currently in the labor force but are not employed. The individual record of employment status is obtained from the Census2000.

Variables Based on Supply-side Argument

Human capital (*schooling variance*) – The variance in the years of schooling can be seen as an indicator of human capital dispersion. Since IPUM data only provides the categorical measure on years of schooling for individuals, I recoded this variable into numerical years (See Appendix.A), and then calculated its variance for each MSA.

Age structure (*age variance*) – This variable is measured as the variance of age of MSA labor force. The Census2000 provides individual age data at the year 2000.

Immigrant population (*immigrants*) – The census2000 also record individual immigration status. I use the simple ratio between native born and foreign born population to measure the size of immigration populations, because such a measure shows a normal distribution, while the ratio of foreign to native born population shows an abnormal distribution. Responding to the measure, I expect a negative coefficient. In other words, the higher the ratio a MSA has, the less percentage of immigrant population, and the lower the income inequality.

Racial composition (*Racial diversity*) – I use a multigroup entropy index to measure racial diversity (Michael White, 1986; Iceland, 2004). The higher value indicates a more diverse population. The IPUM data provides the single race identification data (racesing), which includes five racial categories – White, Black, American Indian, Asian or Pacific Islander, and other. The data also specifies the subcategory of Hispanic under the White category. Since American Hispanics are considered as a minority population in most sociological studies, I recode it as a separate category in my analysis. Thus, the entropy index used here is based on 6 racial categories.

Measures of Control Variables

To exclude effects of metropolitan population size and geographic locations, I add two control variables in the OLS regression, and both are calculated from IPUMS data:

Total population (*log population*) – The natural log of total population of the labor force is used to measure the size of the MSA.

Region (*North*) – A dummy variable is equal to 1 if a MSA is located in either the Northeast or in Midwest, otherwise it is equal to 0.

CHAPTER IV

METHODS

OLS Regression

I use ordinary least square (OLS) regression to test the hypotheses on income inequality. The preliminary analysis shows that the data has some heteroskedasticity problem, but not severe[3]. I will investigate this issue in future analysis. Since the model includes thirteen independent variables, I suspect that there is the problem of multicollinearity, and some independent variables may have indirect effects on income inequality. Therefore I incorporate the path model in the following section to address the causal effect among independent variables. Finally, one of the advantages of using the Theil index is to inspect the components of total inequality though decomposition. It can provide measures of within-group and between-group inequality. Thus, I include Theil decomposition at the end to examine how demographic configuration of the labor force influences inequality measures.

Path Analysis

Path analysis was first introduced to sociologists by Duncan (1966), and later Alwin and Hauser (1975) gave further explanation on total, direct, and indirect effects. The total effect of one variable on another is not their zero-order correlation, but the

[3] For the OLS regression model that includes all variables, Cameron & Trivedi's decomposition of IM-test for heteroskedasticity is significant at the level 0.01, but Breusch-Pagan / Cook-Weisberg test for heteroskedasticity is not significant.

association of the two not due to common causes; the indirect effects are the part of the total effect that are medicated by other variables; and the direct effects are the part of total effect that are not mediated by other variables (Alwin and Hauser, 1975). In other words, the total effect equals to the sum of the direct and indirect effects in the standard form. Path analysis can efficiently illustrate a causal model in a graph, especially the causes and the effects through the intervening variables. In addition, the computation of direct and indirect effects is relatively simple with the standard coefficients of OLS regression. Since in this study I intend to test multiple hypotheses and cover a broad range of independent variables, it is possible that some independent variables are correlated and have mediated effects on the dependent variable through other independent variables. Thus, applying path analysis is appropriate in that the direct and indirect effects on metropolitan income inequality can be simultaneously examined and easily compared.

Decomposition of the Theil Index

The Theil index is used here to measure metropolitan overall earned income inequality. Although the Gini index is a popular measure and has been widely used to describe the national and regional inequality trends over time, there are several advantages of using the Theil index in the present study: 1) the Theil index satisfies more criteria of the inequality measure than the Gini index (see the detailed discussion in page 38-39); 2) it is very easy to apply decomposition to the Theil index, while the decomposition of the Gini index is less consistent and can be mathematically complicated (Yao, 1999); and 3) the Theil index is highly correlated with the Gini index. For instance, the correlation of the Theil index and the Gini index in my data is 0.976.

The equation to calculate the Theil index is $T = \sum p_i r_i \ln (r_i)$, where the subscript i is used to underscore individual-level recode. Here $p_i = (1/N)$, where N is the metropolitan area's total population, and r_i is the income ratio of individual i (i's income divided by the mean income for the metropolitan area) (for the details about the equation, see Firebaugh, 2003). Since the Theil index requires taking the logarithm of individual income, I add 1 (U.S. dollar) on incomes that equals 0. The Theil index is zero when and only when the income ratio is 1.0 for all individuals. In other words, the Theil is zero under perfect equality. Figure 4.1 shows the histogram of the Theil index for total income inequality for 297 MSA areas. The variance of this variable is .003, with mean at .455 and standard deviation of .055.

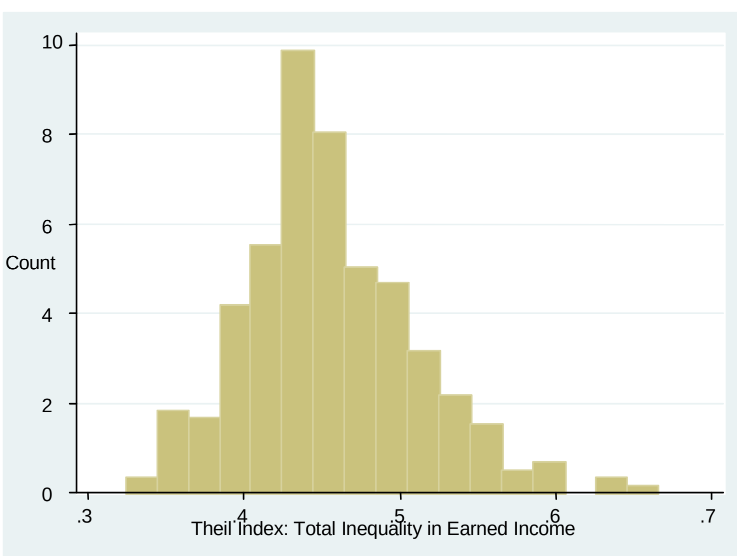


Figure 4.1 Histogram of the Theil Index for Total Income Inequality

One of the most important qualities of the Theil index is its decomposability of the additive between-group and within-group components as follows:

$$T = \sum y_i \ln (y_i / p_i) + \sum y_i T_i$$

Where j indexes population groups (for example, race), y_i is the income share (group j's total income as a proportion of total income for the entire population), and T_i is the level of inequality in group j as measured by the Theil index (Firebaugh, 2003). Specifically, when j indexes race, y_i is a racial group j's income as a proportion of total income in a metropolitan area, p_i is racial group j's population share in a metropolitan's total population, and T_i is the level of inequality within racial group j as measured by the Theil index.

Firebaugh (2003) pointed out that weighted and unweighted between-group Theil measures generate very different results. The between-group inequality measure can be expressed in a general from:

$$I = \sum Wj^* f(Rj),$$

Where Wj indicates weight, R indicates income ratio between group-mean income and population-mean income. For unweighted inequality, Wj equals 1/N, where N denotes the number of categories. For weighted inequality, Wj equals Pj, where Pj denotes the population share for a category. Unweighted inequality is the simple average of f(Rj), telling us about the average difference **between groups**, i.e. male and female. However, weighted inequality is the population-weighted average of f(Rj), telling us average difference **between individuals'** income ratios (Firebaugh, 2003, page 131). In other words, unweighted inequality is only determined by mean income of each group, but weighted inequality is determined by both mean of group income and the population share of each group.

CHAPTER V

OLS REGRESSION AND RESULTS

In this chapter I first summarize the major hypothesis in the regression model, then provide the descriptive results for the measures, and finally report the results of OLS regression analysis.

Hypotheses

Based on literature reviewed earlier, I expect:

1. Unionization reduce overall income inequality;

2. Passing Right-to-work laws increases overall income inequality;

3. Higher minimum wage reduces overall income inequality;

4. Better public education systems reduce overall income inequality;

5. Deindustrialization increases overall income inequality;

6. More stratified occupational structure increases income inequality;

7. More jobs in the public sector reduce overall income inequality;

8. Racial inequality increases overall income inequality;

9. Higher unemployment rate increases overall income inequality;

10. Larger variance in human capital among working population increases overall income Inequality;

11. Larger age variance among a working population increases overall income inequality;

12. A large immigrant population increases overall income inequality;

13. A racially diverse population increases overall income inequality;

Descriptive Analysis

Table 5.1 lists the descriptive statistics for the dependent and independent variables.

Table 5.1 Descriptive statistics

	Descriptive statistics				
	Obs	Mean	Std.Dev	Min	Max
Theil index	297	0.455	0.055	0.324	0.666
Union coverage	233	14.324	7.742	0.600	38.200
RTW laws	297	0.421	0.495	0.000	1.000
Minimum wage	297	4.949	0.901	2.000	6.500
Public education	297	7.985	1.546	4.698	13.519
Production industry	297	0.151	0.048	0.057	0.343
Occupational differentiation	297	0.990	0.002	0.964	0.992
Public sector jobs	235	0.165	0.065	0.029	0.452
W/B income ratio	297	1.459	0.219	0.608	2.590
Unemployment	297	0.059	0.019	0.023	0.142
Age variance	297	182.378	10.414	151.159	218.325
Schooling variance	297	10.010	2.779	5.498	20.654
Immigrants	297	18.426	15.615	0.592	79.220
Racial diversity	297	0.558	0.234	0.083	1.203
Log population	297	9.073	1.015	7.492	12.254
North	297	0.423	0.495	0.000	1.000

OLS Regression Results

The results of OLS regression models are summarized in Table 5.2 to Table 5.3. Most independent variables have significant effects on the Theil index. However, the amounts of variances in inequality explained by the three groups of variables are different. Both demand-side and supply-side factors can explain over 50% of variance in inequality by themselves, while the political-economic factors only explain 23%. Furthermore, almost all independent variables from demand and supply arguments are significant, while only one public economic variable in the full model is significant. I explain the coefficient for each independent in detail in the following section.

Table 5.2 Regression Coefficients of Independent Variables on Theil Index

	Political economic	Demand side	Supply side	W/O control	Full model
Union coverage	-0.000			-0.000	-0.000
	(.000)			(.000)	(.000)
RTW laws	0.010			0.018**	0.012
	(.010)			(.007)	(.007)
Minimum wage	-0.001			-0.003	-0.005
	(.004)			(.003)	(.003)
Public education	0.010**			0.001	0.004*
	(.003)			(.002)	(.002)
Production industry		-0.502**		-0.425**	-0.383**
		(.072)		(.670)	(.067)
Occupational differentiation		-1.764		3.702**	3.178*
		(1.472)		(1.300)	(1.306)
Public sector jobs		-0.119**		-0.147**	-0.153**
		(.046)		(.040)	(.042)
W/B income ratio		0.062**		0.038**	0.046**
		(.013)		(.012)	(.012)
Unemployment		1.260**		1.283**	1.258**
		(.172)		(.169)	(.167)
Age variance			0.002**	0.001**	0.001**
			(.000)	(.000)	(.000)
Schooling variance			0.012**	0.010**	0.010**
			(.001)	(.001)	(.001)
Immigrants			0.000*	0.001*	0.001*
			(.000)	(.000)	(.000)
Racial diversity			0.022	-0.019	-0.039*

Table 5.2 Continued

	Political economic	Demand side	Supply side	W/O control	Full model
			(.014)	(.015)	(.016)
Log population	0.006	0.005	0.003		0.003
	(.003)	(.003)	(.003)		(.003)
North	-0.057**	-0.022**	-0.025**		-0.025**
	(.010)	(.006)	(.005)		(.008)
R2	0.226	0.524	0.545	0.674	0.692
N	233	235	297	233	233

*p<.05; **p<.01(two-tailed tests) . Standard error in parentheses.

Table 5.3 Beta Coefficients of Independent Variables on Theil Index

	Political economic	Demand side	Supply side	W/O control	Full model
Union coverage	-0.043			-0.058	-0.025
RTW laws	0.087			0.164**	0.105
Minimum wage	-0.024			-0.045	-0.08
Public education	0.298**			0.042	0.121*
Production industry		-0.402**		-0.342**	-0.308**
Occupational differentiation		-0.070		0.147**	0.126*
Public sector jobs		-0.143**		-0.177**	-0.185**
W/B income ratio		0.240**		0.149**	0.178**
Unemployment		0.445**		0.456**	0.447**
Age variance			0.337**	0.227**	0.240**
Schooling variance			0.587**	0.546**	0.523**
Immigrants			0.118*	0.144*	0.141*
Racial diversity			0.092	-0.078	-0.163*
Log population	0.104	0.083	0.067		0.059
North	-0.517**	0.199**	-0.225**		-0.224**
R2	0.226	0.524	0.545	0.674	0.692
N	233	235	297	233	233

*p<.05; **p<.01(two-tailed tests).

Political Economic Variables

I tested four hypotheses from the political economic perspective. I expect that union coverage, minimum wage, and spending on public education have negative effects on income inequality, and that RTW law has a positive effect. However, the coefficients of these variables in the OLS regression models are inconsistent. Union coverage and minimum wage are not significant in any model, and RTW law is significant only in the model that includes all independent variables but without control variables. Spending on public education is significant in the political-economic-variable-only model and the full model. In short, the effects on income inequality do not seem to be straightforward, and I suspect there is a causal relationship among these independent variables.

To inspect the problem of multi-collinearity, I included the correlation matrix, VIF and tolerance scores for all independent variables in the analysis (See table 5.4 & table 5.5). The results show a moderate correlation for four variables and low tolerance scores for *RTWlaw* and *union coverage*. One solution for multi-collinearity is to combine some variables. Conceptually, both RTW laws and union coverage may directly relate to the degree of unionization, with the former as an obstacle and the latter as an outcome. Technically, both unionization and minimum wage can be considered as indicators of workers' strength, thus it is reasonable to combine the above three independent variables and create a new common variable – workers' strength. Although public education is also based on the political economic perspective and moderately correlates with the other three, it does not belong to the same substantive issue shared by the other three variables. Thus, using factor analysis (Table 5.6), I created a new independent variable and named it workers' strength.

Table 5.4 Correlation among PE Independent Variables

Variables	(1)	(2)	(3)	(4)
1. Union coverage	1.000			
2. RTW law	-0.676	1.000		
3. Minimum wage	0.142	-0.296	1.000	
4. Public education	0.548	-0.558	0.120	1.000

Table 5.5 VIF and Tolerance for OLS Regression Model with All Independent Variables

Variable	VIF	1/VIF
Schooling variance	2.74	0.365
RTWlaw	2.62	0.381
Union coverage	2.60	0.384
Racial diversity	2.57	0.389
Unemployment	2.42	0.414
Immigrants	2.31	0.433
Public education	1.98	0.505
Production industry	1.95	0.512
Occupational differentiation	1.79	0.558
Public sector jobs	1.57	0.638
W/B income ratio	1.52	0.659
Age variance	1.24	0.807
Minimum wage	1.19	0.839
Mean VIF	2.04	2.04

Table 5.6 Factor Scores for Political Economic Independent Variables

Variable	Factor1	Factor2	Uniqueness
Union coverage	0.734	-0.100	0.452
RTW law	-0.785	-0.019	0.384
Minimum wage	0.293	0.200	0.874
Eigenvalue	1.240	0.051	
Difference	1.189	0.289	
R2	163.8**		

The results of these new variables, workers' strength and public education, are shown in table 5.7. As expected, the positive coefficient of workers' strength supports the idea that a metropolitan area where workers have more power, including having more union members, facing no regulation from RTW laws, and benefiting from higher minimum wage, lowers overall income inequality.

Table 5.7 Beta Coefficients of Workers' Strength

Variables	W/O control	Full model
Workers' strength	-0.228**	-0.177**
Public education	0.054	0.125*
Production industry	-0.338**	-0.301**
occupational differentiation	0.149**	0.127**
Public sector jobs	-0.162**	-0.155**
W/B income ratio	0.146**	0.165**
Unemployment	0.458**	0.45**
Age variance	0.230**	0.242**
Schooling variance	0.539**	0.518**
Immigrants	0.153**	0.156**
Racial diversity	-0.069	-0.148*
Log population		0.077
North		-0.187**
N	233	233
R2	0.673	0.688

*p<.05; **p<.01(two-tailed tests).

The coefficient of public education is positive in the full model. This is opposite to what I expected. If higher expenditure per student in elementary and secondary public schools does reflect a better public education system, the result simply proves that the hypothesis is wrong, unless the measure is not a good indicator of public education system. In that case, the possible explanation could be that many students who graduated from elementary/secondary public schools go to colleges and work in other cities or states. In other words, there is no direct link between elementary/secondary public education in a particular area and workers' income in the same area. Therefore, the hypothesis does not hold at the city or metro level, but only can be tested at the regional or national level, assuming college graduates tend to find a job in the same region or nation where they went to college, or controlling for inter-city young adult migration. Further study on this topic is needed.

In sum, PE variables show promising but incomplete results. Early research suggests that workers as one social entity may gain their economic bargaining power together and reduce the income differences among them (Gustafsson and Johansson, 1999). However, such power or strength may be contingent on the extent of unionization and confined by state policies or regulations, as it is shown in this analysis. For the public education system, which is also heavily influenced by local policy and regulations, this effect on inequality does not confirm the conventional view or, at least, is inconclusive.

Demand-side Variables

Table 5.2 shows that in the full model the coefficients for the five demand-side independent variables are all significant. As mentioned in Chapter II, theories, such as the Great U-turn (the extension of Kuznets' curve), dual economy, globalization and information technology, suggest that the shift from the industrial to the post-industrial period, from manufacturing goods to providing service and information, increases income inequality. The negative coefficient of *production industry* provides support for the deindustrialization argument at the metropolitan level. Relevant to industrial restructuring is the increase in occupational categories. The distribution of earnings is suggested to correspond to the stratified occupations (Massey and Hirst, 1999). The result also supports this hypothesis as shown in its positive coefficient. The negative effect of public sector jobs is also consistent with earlier literature and my hypothesis; that is, the more jobs in the public sector, the less income inequality for a metropolitan area. Finally, both racial inequality and unemployment rates show a consistent and positive impact on overall income inequality. Overall, data strongly supports all the demand-side hypotheses.

One particular issue to be addressed here is an outlier case in the distribution of occupational differentiation. Visalia-Tulare-Porterville, CA has the lowest occupational differentiation score, 0.964, and the highest leverage score, 0.689 in the model. Actually, Visalia, CA is a very special case: it is the largest city and economic center of Tulare County, CA, one of the most productive agricultural areas in the U.S. Its market value of agricultural products sold ranked the second in 2002 among all U.S. counties (U.S.

Department of Agriculture, 2000). Compared to other metropolitan areas with a similar size of population, such as York, PA, Modesto, CA, and Reno, NV, occupational distribution of Visalia is heavily concentrated in the category of miscellaneous agricultural workers, including animal breeders. Although this outlier has a large impact on the slope of this variable, the model is robust. Without Visalia-Tulare-Porterville, CA, the coefficient of occupational differentiation is still significant (5.46**), controlling for other independent variables.

Supply-side Variables

On the supply side, as expected, coefficients of variance of schooling and variance of age are positive and significant, supporting the idea that heterogeneity in education and age among workers increases overall income inequality. However, the variable of immigrants, measured as the ratio between native- and foreign-born populations, shows the sign opposite to the hypothesis. In other words, the data suggests that a metropolitan area with a larger native-born population and fewer foreign-born residents has higher income inequality. More interestingly, *racial diversity* seems to have very little effect when other independent and control variables were controlled in the model and this coefficient is also opposite to my hypothesis. Literatures on immigrants, racial composition, and human capital have repeatedly suggested relationships among the three (Reed 2001, Stolzenberg and Tienda, 1977, Sullivan 2006). It is likely there may be direct and indirect effects of immigrants on inequality through racial diversity or variance of schooling. After considering the direct and indirect effects of immigrants, racial diversity may show the expected positive coefficient. To check this possibility, a path analysis is introduced in the next chapter.

CHAPTER VI

PATH ANALYSIS AND DECOMPOSITION

In this chapter I first apply the path model to test the direct and indirect effects of demographic variables and then use the decomposition method to compare the weighted and unweighted between-group Theil inequality index in terms of gender, age, education, and race.

Path Analysis and Its Results

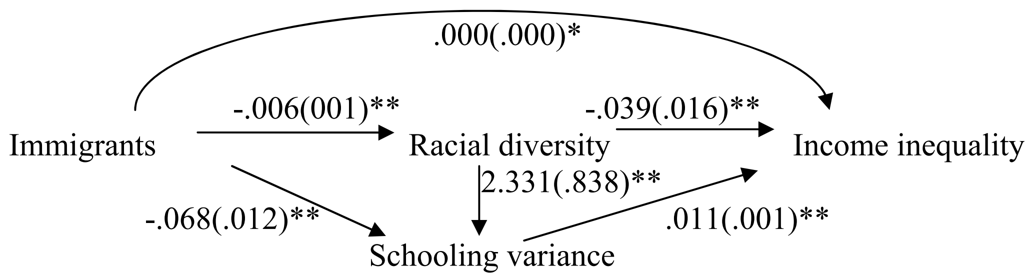
The OLS regression results show that most independent variables have the expected effects on income inequality, but, since the full model includes 13 independent variables, the problem of multicollinearity and causal relationship among independent variables may exist. In Chapter V, I already addressed the multicollinearity problem among political economic variables with factor analysis. In this section I will apply path analysis to explain the supply-side demographic variables.

The positive coefficient for immigrants and the negative coefficient for racial diversity in OLS regression are unexpected, and this suggests that their impacts on inequality may not be as straightforward as I hypothesized and could intervene or be intervened by other independent variables, e.g. variance of schooling. Conceptually, if a city has a large number of immigrants, its racial composition usually tends to be more diverse, which in turn can cause a larger variance in schooling among the population. Furthermore, an immigrant population itself tends to have large variance of schooling. Thus, both racial diversity and immigrant variables could have indirect effect on income inequality through variance of schooling. Following this logic, I incorporated the path model in the following manner (Figure 6.1). When other independent variables are controlled, the total effect of the variable immigrant on overall income inequality is

$$0.141+(-.344)*(-.163)+ (-.344)*(.192)*(.523)+ (-.330)*(.523)= -.01.$$

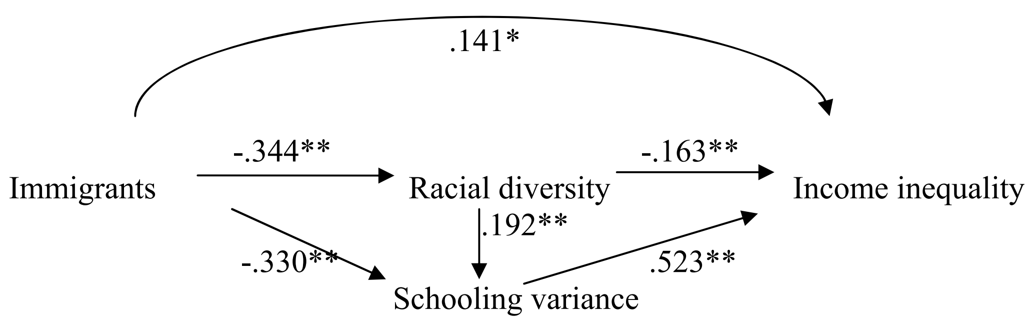
And the total effect of racial diversity on income inequality is

$$-.163+(.192*.523) = -.063.$$



*p<.05; **p<.01(two-tailed tests).

Figure 6.1 Path Model Coefficients with Standard Error in Parentheses



*p<.05; **p<.01(two-tailed tests).

Figure 6.2 Path Model with Standardized Coefficients

The path model shows that variable immigrants, measured as the ratio of native-born to foreign-born population, and variable racial diversity have significant direct and indirect effects on overall income inequality. As expected, a larger native-born population reduces racial diversity (-.344**) and variance of schooling (-.330**), and high racial diversity increases variance of schooling (.192**), and variance of schooling has a large impact on income inequality (.523**). However, there are two coefficients in Figure 6.2 showing unexpected signs. One is the direct effect of immigrants on the Theil index (.141*), and this coefficient indicates that a higher native-born population increases income inequality. Another is the negative sign of racial diversity on the Theil index (-.163**), which means increased racial diversity leads to lower income inequality. Logically, the large numbers of immigrant and non-white populations may influence other aspects of human capital distribution when variance of schooling is held constant, and therefore has a direct inequality-increasing effect. Surprisingly, this analysis reveals an inequality-reducing effect conditioning on equal variance of schooling. This is quite puzzling, since no study or theory has indicated increases in immigrants or racial diversity may reduce income inequality when variance in education of population is controlled. Furthermore, the two unexpected coefficients seem to support each other: a large share native-born population (measured by a simple ratio) increases inequality, and a racial diverse population (measured by the entropy index) reduces it (table 6.1).

A possible explanation is that both variables have a non-linear effect on income inequality. However, I tested this possibility by adding the squared value of immigrants and racial diversity in the model and found their coefficients are not significant either. So there may be other nonlinear relationships that I did not capture in this analysis. Why the two direct effects are opposite to the conventional beliefs will be an interesting question for future studies.

Table 6.1 Beta Coefficients of OLS Regression for Path Analysis

	Dependent variable				
Variables	Theil index	Schooling variance	Racial diversity	Theil index	Theil index
Union coverage	-0.025	-0.151*	0.112	-0.104	-0.111
RTW laws	0.105	-0.218**	0.040	-0.009	-0.012
Minimum wage	-0.080	-0.037	-0.064	-0.100*	-0.096
Public education	0.121*	0.051	-0.004	0.148*	0.149*
Production industry	-0.308**	-0.145*	-0.021	-0.384**	-0.383**
Occupational differentiation	0.126*	-0.289**	0.005	-0.025	-0.025
Public sector jobs	-0.185**	0.146**	-0.020	-0.108	-0.107
W/B income ratio	0.178**	0.083	0.239**	0.221**	0.206**
Unemployment	0.447**	0.105	0.397**	0.501**	0.477**
Age variance	0.240**	-0.020	-0.150**	0.229**	0.239**
Schooling variance	***0.523****				
Immigrants	***0.141****	***-0.330****	***-0.344****	-0.031	***-0.010***
Racial diversity	***-0.163****	***0.192****		***-0.063***	
Log population	0.059	0.140**	0.232**	0.132*	0.118*
North	-0.224**	-0.040	-0.308**	-0.246**	-0.226**
R2	.692	.648	.659	.595	.594
N	233	233	233	233	233

*p<.05; **p<.01(two-tailed tests).

Decomposition of the Theil Index

Levy and Murnane (1992) have suggested that the shift in labor supply played a major role in between-group earnings between early 1970s to late 1980s, (e.g. increases in male workers, young college graduates, and immigrants in the labor force contributed to the increase in inequality during this period). Although their study focused on the trends of national inequality over time, it has an implication on the inequality across areas, because demographic composition of the labor force varies as it does for different time periods. The better way, or maybe an easier way, to understand how population composition influences calculating inequality is to apply the Theil decomposition technique to the data.

Table 6.2 summarizes these demographic characteristics of the sampled population. All data is collected from Census2000 5% sample data. *Sex* variable is coded as male or female. *Age* is recoded into five categories (less than 25, 25-34, 35-44, 45-54, 55 and over), based on the reported persons' age in years as of the last birthday. *Education* reports the highest level of respondents' educational attainment, including five categories - no high school diploma, high school diploma, some college or associate college degree, Bachelor's degree, and Post-graduate degree. *Race* is reclassified into six categories according to the IPUMs single race variable (racesingd), including White, Hispanic, Black, Asian, Native American, and Other.

Table 6.2 Frequency Statistics for Demographic Variables

		Frequency	Percent	Cumulative Percentage
Sex	Male = 1	2,557,105	52.90	52.90
	Female = 2	2,276,397	47.10	100.00
Age	Age less than 25 = 1	741,301	15.34	15.34
	Age 25 to 34 = 2	1,097,251	22.70	38.04
	Age 35 to 44 = 3	1,273,393	26.35	64.38
	Age 45 to 54 = 4	1,057,219	21.87	86.26
	Age 55 and above = 5	664,338	13.74	100.00
Education	No high school diploma = 1	747,084	15.46	15.46
	High school diploma = 2	1,207,904	24.99	40.45
	Some college or associate degree = 3	1,509,789	31.24	71.68
	Bechelor's degree = 4	876,096	18.13	89.81
	Postgraduate degree = 5	492,629	10.19	100.00
Race	White	3,725,832	77.08	77.08
	Hispanic	268,090	5.55	82.63
	Black	563,963	11.67	94.30
	Native American	30.869	0.64	94.94
	Asian	237,213	4.91	99.84
	Other Race	7,535	0.16	100.00

Figure 6.3 to Figure 6.6 illustrate the weighted and unweighted between-group income inequality based on gender, age, education, and race. Figure 6.4 shows that weighted and unweighted income inequality over age groups are highly correlated, meaning age distribution does not influence weighted between-age-group income inequality. In other words, population compositions of age across MSAs are relatively consistent.

On the other hand, Figure 6.6 shows that race composition has the largest impact on weighted racial income inequality. For example, New York-Northeastern, NJ has a relatively low unweighted inequality, but since it has a diverse racial population (Whites only count for 55% of the total population), its weighted inequality becomes the highest.

On the other hand, Williamsport, PA has the highest unweighted between-group inequality, but 98.3 percent of its population is White, and its weighted inequality becomes much smaller. This graph also suggests that racial compositions across U.S. MSAs are highly inconsistent.

For inequality in sex and education, unweighted and weighted numbers shows moderate correlation (correlation coefficient for sex is 0.619 and for education is 0.182). This implies population compositions of sex and education have to some extent, an impact on how we measure between-group income inequality.

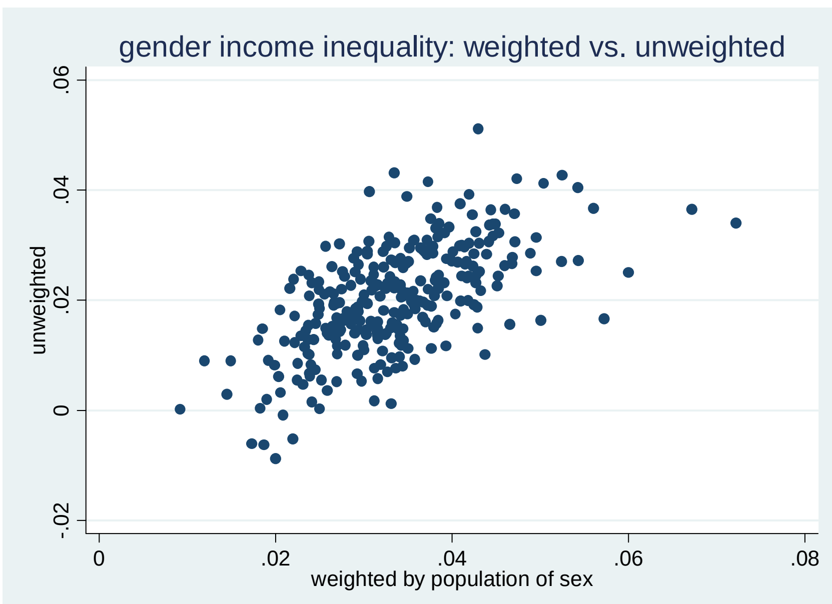


Figure 6.3 Between-group Gender Income Inequality

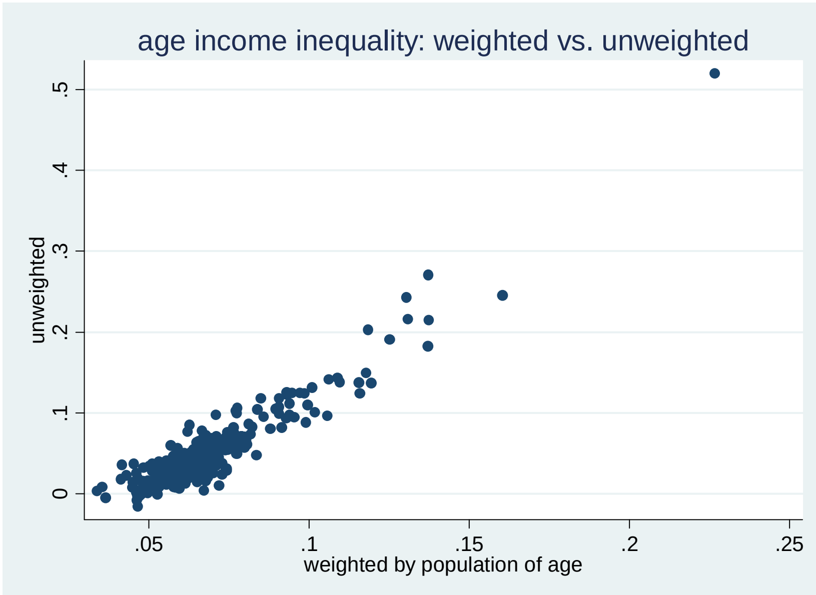


Figure 6.4 Between-group Age Income Inequality

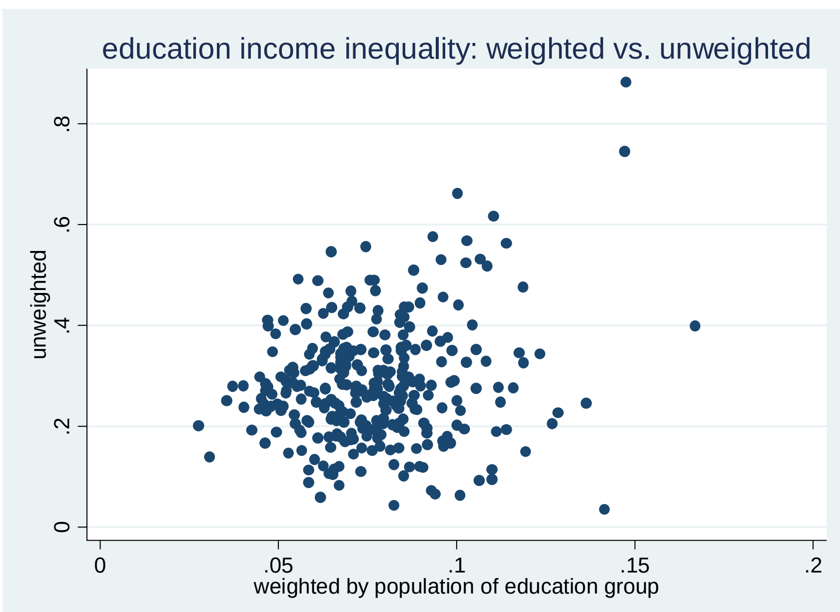


Figure 6.5 Between-group Education Income Inequality

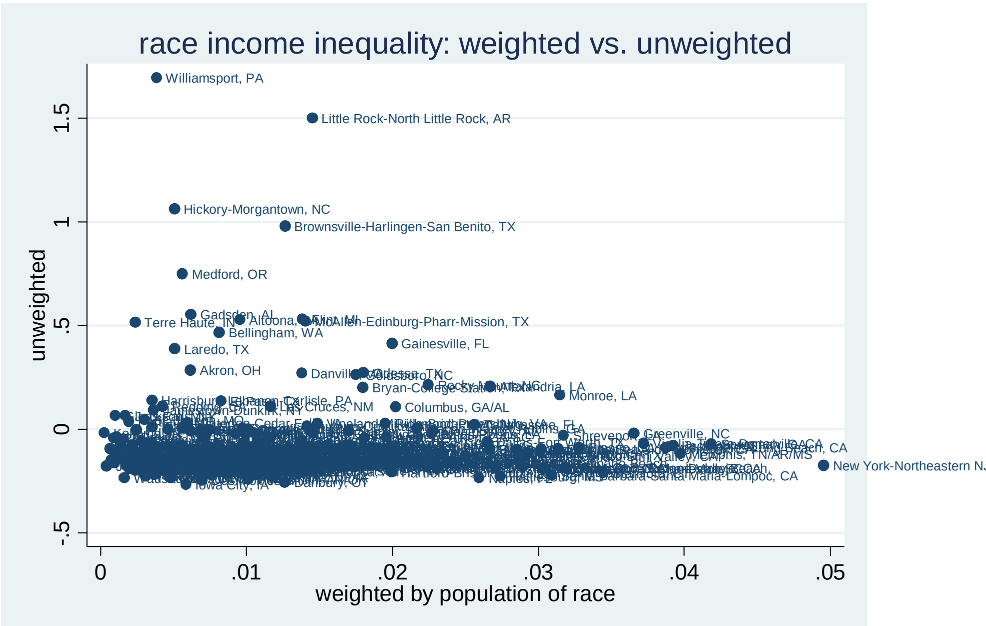


Figure 6.6 Between-group Race Income Inequality

CHAPTER VII

CONCLUSIONS

Summary

The goal of this research project is to document the causes of income inequality in U.S. metropolitan areas. I started with reviewing three major perspectives and then developed thirteen hypotheses. The results of OLS regression models support most of my hypotheses and show strong effects of demand-side and supply-side variables[4]. The Beta coefficients indicates that schooling variance of the labor force has the largest impact on MSA income inequality (.523), followed by unemployment rate (.447), the size of production industry (-.308), age variance of the labor force (.240), public sector jobs (-.185), White and Black income ratio (.178), racial diversity (-.163), and immigrant population (.141). By contrast, political-economic independent variables have very limited effects. Only when three of its variables are combined together does the effect become significant. To a great extent, the regression analysis has efficiently answered my main research question. The full model explains almost 70 percent of variance in dependent variables, and provides support for ten out of thirteen hypotheses.

However, including the large number of independent variables in one regression model is very likely the cause of the multicollinearity, as it is the case in the supply-side variables in this study. Since data show immigrant population, racial diversity and variance of schooling are moderately correlated, and literature has also suggested the

[4] The results from the re-estimation of OLS regression on supply variables using the subsample of 233 cases are fundamentally the same as those in Table 5.2. Therefore, the comparison of model fitness across regressions is valid.

causality among the three, I included a path analysis in Chapter VI to examine their direct and indirect effects on income inequality. The results clearly show that racial diversity mediates the effect of immigrants and that variance in schooling mediates the effects from both immigrants and racial diversity. The path model also indicates that variance of schooling in metropolitan areas has the strongest direct effect, while the effects of other supply-side factors are comparably small, and most likely through variance of schooling. I am most concerned with the direct effects of immigrants and racial diversity for they seem to run contrary to my hypotheses. One possibility is that measurement error in immigrants and racial diversity lead to the unexpected findings, and another could be that the relationship between immigrants, racial diversity, and income inequality is simply not a linear one. If that is the case, the results of this project definitely casts some doubt on the conventional view of racial composition and inequality.

The final step of this study was to understand how population composition influences between-group income inequality. I compared the weighted and unweighted inequalities based on sex, age, education, and race groups. The main finding is that when between-group inequality weighted by group population size, racial composition changes the between-group inequality measure considerably, while age composition changes it slightly and gender and education composition changes it moderately.

Implications

This research utilizes multiple data sources and statistical methods to investigate the causes of U.S. metropolitan income inequality around the year 2000. Although the main research question is simple, the results provide some significant implications for future studies. First, metropolitan income inequality is not determined by a single factor, but is involved with a variety of political, economic and demographic causes. Scholars from different fields usually focus on certain variables most relevant to their disciplines while ignoring other variables, but this study has given an excellent example of how to bring cross-disciplinary theories and concepts into a model which may result in better outcomes and improve our understanding on the subject.

Second, the regression model shows that supply-side factors explain most variance in dependent variables, and that one supply-side factor, schooling variance, has the highest Beta coefficient among all independent variables. This finding suggests that changes in human capitals among working population could increase or reduce income inequality significantly when other causes are unchanged. Hypothetically, reducing schooling variance by providing workers more opportunities for higher education and training will be an effective solution for areas with high income inequality.

Third, the findings from path model analysis cast doubt on the popular assumption that immigrant and racial diversity introduce inequality and suggest further study to address the relationship between these variables. The answer to the question why immigrants and racial diversity reduces inequality when schooling variance is controlled can be provided by a specifically designed research project, but is beyond the scope of this study.

Finally, decomposition analysis suggests that population composition can substantially change the value of between-group income inequality, and this effect is most significant for between-race inequality measures. In other words, using weighted or unweighted measures can lead to different results and interpretations for the same study. Thus, researchers should choose an appropriate measure most suitable to their research questions.

There are also a few limitations of this study. The measures of some variables could be problematic in hypothesis testing. For example, the expenditure per student in public schools may not accurately measure the quality of public education system in a particular area, and therefore it is hard to draw the conclusion based on its coefficient. Unfortunately, I cannot find a better and more reliable data to measure this variable. I am also concerned with the causal effects of immigrants and race on income inequality. There are several possible reasons for the unexpected results. The racial diversity measure cannot distinguish between certain types of low-diversity metropolitan areas. For instance, the majority of population in El Paso and San Antonia are Latinos, but in most other cities white is majority population. Their racial diversity scores may have similar low or (medium) values, but the ethnic composition of the cities may have different implications for inequality. Second, both immigrants and racial diversity could have unlinear effect on income inequality. As indicated in Kuznets' Curve, when a variable is proportion (e.g. the degree of industrialization), its effect on inequality could be U or inverted U shape. Obviously this study has not been able to give a clear answer on the effect of immigrants and racial diversity and further research may provide more information. Finally, this study only used cross-sectional data, an approach that does not control for all possible causes of metropolitan income inequality. The analysis of panel data will be superior in that particular characteristics of metropolitan areas which are relevant to income inequality and persist over time can be controlled.

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APPENDIX A

RECODE IPUMS EDUCATION CATEGORY INTO YEARS OF SCHOOLING

EDUD99

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No school completed	39983	.8	.8	.8
	1st-4th grade	22513	.5	.5	1.3
	5th-8th grade	132904	2.7	2.7	4.0
	9th grade	92727	1.9	1.9	6.0
	10th grade	136160	2.8	2.8	8.8
	11th grade	158346	3.3	3.3	12.1
	12th grade, no diploma	164451	3.4	3.4	15.5
	High school graduate, or GED	1207904	25.0	25.0	40.4
	Some college, no degree	1166321	24.1	24.1	64.6
	Associate degree, occupational program	343468	7.1	7.1	71.7
	Bachelors degree	876096	18.1	18.1	89.8
	Masters degree	324574	6.7	6.7	96.5
	Professional degree	113030	2.3	2.3	98.9
	Doctorate degree	55025	1.1	1.1	100.0
	Total	4833502	100.0	100.0	

.

Therefore, I recode this variable as:
No school completed – 0
1-4 grade – 2.5 (years of schooling)
5-8 grade – 6.5
9th grade – 9
10th grade – 10
11th grade – 11
12th grade, no diploma – 11.5
High school graduate, or GED – 12
Some college, no degree – 13
Associate Degree, occupational program – 14
Bachelor degree – 16
Masters degree – 16+2.5 = 18.5
Professional degree – 16+8=24
Doctorate degree – 16+7.5 = 23.5

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