EARNINGS INEQUALITY IN U.S. METROPOLITAN REGIONS: THE ROLE OF THE FINANCIAL SERVICES AND INFORMATION TECHNOLOGY INDUSTRIES

by

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DEDICATION

To Professor John Petersen, a sensible Keynesian.

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ABSTRACT

EARNINGS INEQUALITY IN U.S. METROPOLITAN REGIONS: THE ROLE OF THE FINANCIAL SERVICES AND INFORMATION TECHNOLOGY INDUSTRIES

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George Mason University, 2013

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This dissertation presents annual measures of earnings inequality for 255 metro regions in the U.S. for the years 1990 to 2004. Measures of industrial structure are also calculated for each metro to observe whether there is an association generally between industrial structure and earnings inequality, with particular attention paid to the role of the financial services and information technology industries. It is found that while the financial services industry made a clear and significant contribution to the growth of earnings inequality in metro regions, the role of the information technology industry is not clear. It is instead found that the professional & business services industry—in addition to financial services—made an important contribution to the growth of earnings inequality in metro areas over the 1990 to 2004 period. These findings have important implications for financial regulatory and corporate governance policies.

CHAPTER 1: INTRODUCTION

Since the early 1970s, income inequality in the United States has typically been higher and grown more rapidly than in any other advanced industrial nation. Evidence for this can be seen in data from the Luxembourg Income Study (LIS), presented in Figure 1 on the next page. These data show comparable measures of household income inequality for the U.S. and a number of other advanced industrial nations. The position of the U.S. relative to the other nations is clear: for several decades, income inequality in the U.S. has been the highest in the developed world.[1] (Luxembourg Income Study, http://www.lisproject.org/keyfigures.htm)

In addition to the LIS measures of income inequality for the U.S.—which are based on household income data from the U.S. Census Bureau—economists Thomas Piketty and Emmanueal Saez have calculated measures of income inequality based on data from individual tax returns. As an indicator of income inequality, Piketty and Saez have measured the proportion of total national income going to individuals in the top 10 percent of the income distribution for the years 1970 to 2006. As shown in Figure 2 on

[1] The same holds true for earnings inequality, which has typically been higher in the U.S. than other developed countries. See Gottschalk and Smeeding, "Cross-National Comparisons of Earnings and Income Inequality," *Journal of Economic Literature* 35 no.2 (1997). It should be noted that while *earnings* includes wages, salaries, and bonuses—i.e. any income related to working—total *income* also includes returns on investments—such as interest, dividends, rents, and capital gains—as well as government transfers and private retirement income.

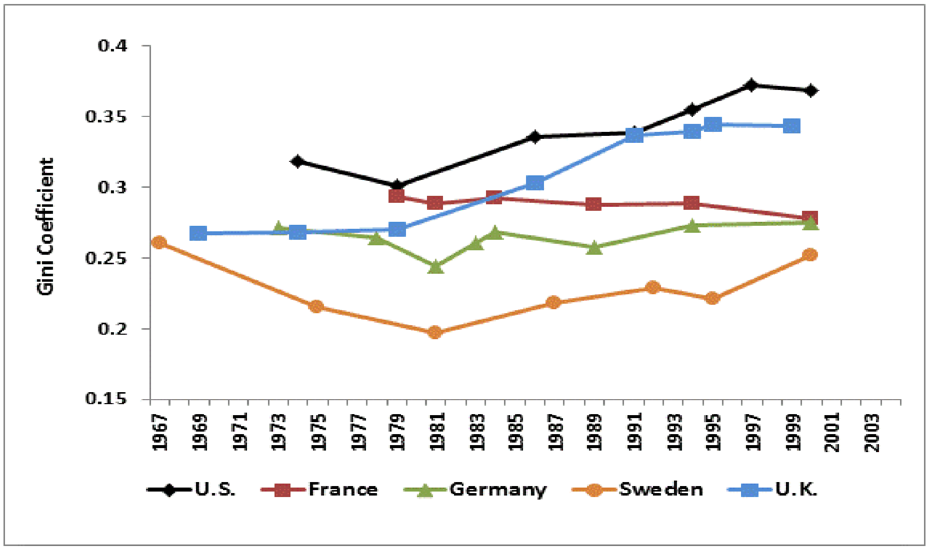

Figure 1: International Comparisons of Household Income Inequality: U.S. and Select Members of the OECD (1967 – 2004)

Source: Luxembourg Income Study

page three, the proportion of total income going to the top 10 percent of the income distribution in the U.S. increased steadily from 31.5 percent in 1970 to 45.3 percent in 2006. Also shown in figure #2 is the growth of *earnings* inequality in the U.S., which follows a very similar pattern. This suggests that the growth of income inequality in the U.S. has, at least in part, been driven by the growth in earnings inequality in the nation over the last several decades. (Piketty and Saez 2003 and 2006); (http://emlab.berkeley-.edu/users/saez/, downloaded January 2009) It should be noted, however, that at least part of the jump in measured inequality between 1986 to 1988—particularly for income—was due to the Tax Reform Act of 1986. This law lowered the top individual income tax rates significantly, which caused more small businesses to file their returns as individuals rather than under the corporate tax schedules.

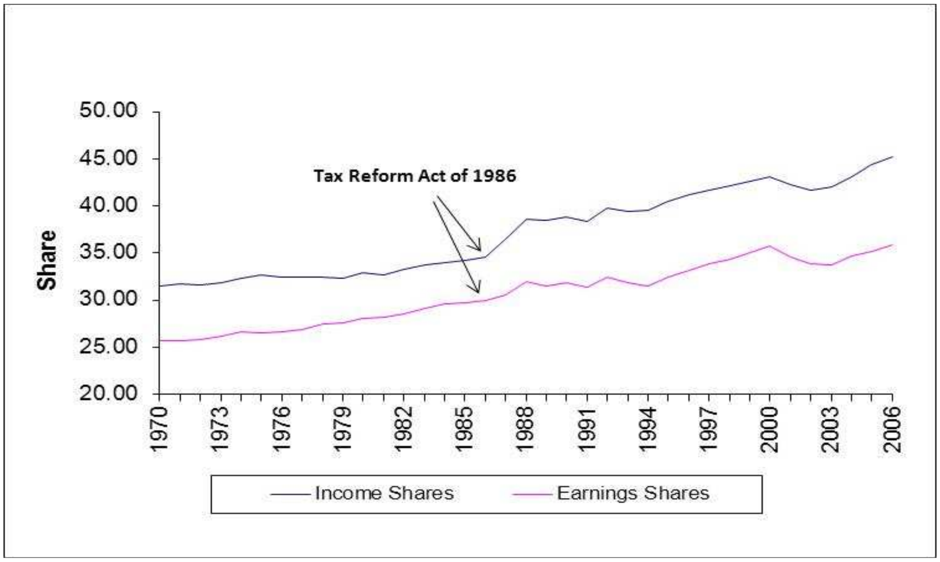

Figure 2: Top Decile Share of Total National Income and Earnings, 1970 – 2006

Source: Piketty and Saez

Income and Earnings Inequality as an Economic and Social Problem

While high and growing levels of income and earnings inequality in the U.S. may be a generally-accepted empirical fact, there is nevertheless an ongoing debate regarding the extent to which it represents a real and significant social problem, and therefore, a legitimate issue for public policy. For economists, a key question to be resolved is whether the level of income inequality has a direct impact on the rate of economic growth. The Neoclassical economic view holds that a higher level of income inequality—all else equal—leads to a higher rate of economic growth. This is due to the fact that the rich have a higher marginal propensity to save than the poor, and thus generate a higher level of aggregate savings in the economy. A higher level of aggregate savings, moreover, leads to greater levels of investment, capital accumulation, and economic growth. (Thorbecke and Charumilind, 2002, pp. 1480-1483) In contrast, a Keynesian argument commonly made is that higher levels of income inequality lead to lower rates of economic growth. This is due to the negative effect of income inequality on aggregate demand. Where fewer people exist with incomes sufficient to buy the goods and services the economy provides, overall economic activity is reduced. (Galbraith, 2001, p. 257-258)

There are additional economic arguments which maintain that higher levels of inequality lead to higher rates of economic growth. One example rests on the belief that the high level of inequality in the U.S. today is a reflection of an increase in innovation. In a Schumpeterian analysis, an increase in innovation creates higher incomes for the innovators—and an increase in inequality—but also translates into higher rates of economic growth. (Feldstein, 1999, p. 35) Another argument in favor of inequality argues that the rise in return to skill in the U.S. economy—which in their view has caused income inequality to rise—has encouraged many workers to pursue higher levels of education; and the consequent growth in the average education level in the U.S. has been an important source of productivity and economic growth. (Becker and Murphy, May/June 2007) In other words, income inequality—and more specifically, earnings inequality—provides the incentives necessary for an economy to grow and prosper. In any case, efforts to reduce income inequality, such as through a generous welfare state, reduces the incentive to work, and thus productivity and economic growth. (Jencks, 2002, p. 50, 53)

Beyond its effect on economic growth, another common economic argument made *against* inequality is its effect on poverty rates. In many peoples' minds, higher income inequality is strongly associated with higher poverty rates. (Sen, 1992, 102-107); (Gundersen and Ziliak, 2004); (Iceland, 2003); (Lewis and Ulph, 1988). One way the relationship between income inequality and poverty can be demonstrated is by examining the association between economic growth and poverty rates and observing how this association has changed over time. Iceland (2003) has pointed out that during the 1950s and 1960s in the U.S. there was a strong inverse relationship between the rate of economic growth and poverty rates. In the 1970s and 1980s, however, this relationship weakened significantly, as poverty rates no longer fell as dramatically during economic expansions as they had previously. The weakening of this relationship, moreover, has been attributed in part to the rise in income inequality.

While there may be no clear consensus among economists regarding the effects of income inequality—good or bad—when viewed beyond the strict discipline of economics, the literature on the potentially *negative* social effects of high levels of income inequality is vast. As pointed out by Thorbecke and Charlumilind (2002), discussions regarding the potentially negative social effects of income inequality come from a variety of fields, including: sociology, political science, psychology, public health, and even criminology. For example, the essentially sociological argument has been made that poverty, in addition to being measured in an absolute sense, should also be seen as a relative phenomenon. People with incomes that are sufficient to meet their basic needs can still be considered to be living in conditions of poverty if their living standards fall far below the rest of the population. (Galbraith, 1958, 251) This is due to the fact that being poor in a rich country, as opposed to being poor in a poor country, requires more income to achieve the same level of social functioning. (Sen, 1992, 115) A high level of income inequality, therefore, can mean that even when rates of absolute poverty are low, rate of 'relatives' poverty may be high.

A related argument is that people pay more attention to their relative as opposed to absolute position in society, as it is their relative position that determines their social status. Moreover, a low social status can lead to feelings of frustration, depression, or anxieties which in turn produce physiological responses in people that may damage their physical health. (Kawachi and Kennedy 2002, 51-52); (Wilkinson 2005, 87) There is, moreover, some empirical support for this hypothesis. The famous Whitehall studies of British civil servants found that death rates, controlling for age, were significantly higher for the lowest level office workers compared to their more senior colleagues. (Wilkinson 58); (Bezruchka 2005) Moreover, a study by J.W. Lynch published in the *American Journal of Public Health* found that higher income inequality across metropolitan areas in the U.S. was positively associated with increased mortality rates at all per-capita income levels. (Ram, 2005)

Another important social implication of high levels of inequality is its potential to promote economic segregation. Indeed, Paul Jargowsky (1996) has found that economic segregation increased in the U.S. for Whites, African-Americans, and Hispanics in the 1970s and 1980s, but particularly for African-Americans and Hispanics in the 1980s. Among other things, economic segregation may lead to the concentration of poverty in inner cities. Wilson (1987) famously argued that high spatial concentrations of poverty in inner-city areas can promote a degree of social isolation which, among other things, makes it more difficult for residents to find jobs in mainstream society. Such concentration may also engender patterns of behavior that are not conducive to establishing a solid work history.[2] (pp. 60-61)

It has also been argued that there may be an inverse relationship in American society between income inequality and the strength of its social contract. Observers such as Lipset (1997) have argued that Americans have traditionally valued a level of egalitarianism in terms of their social arrangements. Moreover, Alexis de Tocqueville in *Democracy in America* argued that, among other things, it was the equality of conditions that had initially allowed democratic institutions to take root in America. (DeTocqueville, 1969) It might be suggested, then, that a high degree of social

[2] It should be noted that in Wilson's view, the theoretical concept of social isolation is distinct from the concept of the culture of poverty.

inequality, of which income inequality is a type, threatens the American social contract and undermines the legitimacy of its established political and social order.

Income and Earnings Inequality in the Metropolitan Context

While it may often be difficult to empirically demonstrate the negative social consequences of income inequality, the fact that it is considered to be of great importance throughout the social sciences—particularly in conjunction with the study of social inequality—means that it is certainly deserving of continued and careful study. Moreover, while income inequality has been studied extensively at the national level in the U.S., much less empirical work has been done examining some of its *spatial* dynamics. The importance of the spatial dimensions of inequality has been noted by observers such as Chakravorty (1996) who points out that: "There is little doubt that the spatial concepts of proximity, contiguity, and distribution impact everyday concerns from rents to the quality of services."

There are of course many ways to examine the spatial dimensions of inequality, which include analyzing it at the state, county, or metropolitan level. Measuring it at the metropolitan level is appealing, however, as metros typically represent one market—albeit often segmented—for things such as labor, housing, and consumer goods and services. This makes them ideal for exploring some of the potentially negative implications of high levels of inequality within a given spatial context. One very important potential implication suggested here, moreover, has to do with the fact that income inequality in the U.S. in recent years has been driven by the growth of incomes at the very top of the income distribution. The growth of high incomes among a subgroup of a population living in a metropolitan region, moreover, may be a key force driving up the general cost of living in those metropolitan regions. This higher cost of living is most strongly reflected in housing prices, which have been bid up by the new higher-income residents to levels beyond what lower- and even many middle-income residents are able to pay.

Conclusion and Plan of Work to Follow

In general, it is clear that the study of income and earnings inequality remains a relevant field of social inquiry generally, both within the economics profession and in the wider world of social science. In addition, compared to the national-level studies, relatively little work has been done examining the phenomenon at lower geographical scales, such as the metropolitan level. It is at the metropolitan level, moreover, that high levels of income inequality may have the clearest and most direct impact on the general social welfare.

In light of this, what follows is an examination of the level and growth of earnings inequality within metropolitan regions in the U.S. for the 1990 to 2004 period. Comparable measures of earnings inequality are calculated annually for each of 255 metro regions for each year of the period.[3] Measures of industrial structure are also calculated for each metro to observe whether there is an association generally between industrial structure and earnings inequality, with particular attention paid to the role of the financial services and information technology industries. It is, in fact, the central hypothesis of this study that those metropolitan regions with the highest levels and strongest growth of earnings inequality over the 1990 to 2004 period have industrial structures significantly weighted toward the high-wage information technology and/or financial services sectors. Moreover, it is these sectors which are largely responsible for the level and growth of earnings inequality in those metropolitan regions.

The following chapter—Chapter 2—provides a review of the theoretical and empirical literature on income and earnings inequality in the U.S., including national studies as well as studies at the state, county, and metropolitan levels. Chapter 3 reviews the theoretical model and hypotheses to be tested in this study, as well as the specific research questions to be answered. Chapter 4 describes the data and methodology utilized to test the hypotheses and answer the research questions, as well as some of the potential issues involved in measuring and analyzing income inequality. Chapter 5 presents the empirical results of the study, including both a descriptive analysis as well as the presentation of a statistical model. The work closes with Chapter 6, which provides the theoretical and empirical conclusions, as well as the policy recommendations.

[3] Seven States—representing 82 metro areas out of a total of 337—did not provide access to data for their metros.

CHAPTER 2: INCOME AND EARNINGS INEQUALITY: THE THEORETICAL AND EMPIRICAL LITERATURE

Introduction

This chapter provides a review of the theoretical and empirical literature on income and earnings inequality. The review of the theoretical literature is not necessarily focused on the U.S. context, although economists in the U.S. have played a central role in the development of inequality theory over time. The review of the empirical work is, however, focused exclusively on the U.S. case and in particular on the studies of inequality conducted since the 1980s. These studies were primarily done at the national-level, although work has been done at the state, county, and metropolitan levels as well. For both the theoretical and empirical reviews, a general effort is made to put ideas and developments in their historical context, allowing for a clearer picture of how things have evolved over time.

Ricardo and Classical Theory

The early economic literature on income and earnings inequality, beginning with the Classical period of the early 19th century, is almost purely theoretical. Empirical work on the topic was difficult due to the scarcity of reliable data with adequate coverage of the population. In fact, in the United States, it was not until the 1950s that tax returns covered more than a small proportion of the total population. (Kuznets, 1953, p. xxix) It is nevertheless useful to review some of the earlier theoretical work, as it continues to influence not only current theories of inequality, but the direction of empirical research in the field.

As is well-known, Ricardo (1821) was particularly interested in the theory of the income distribution, having noted that uncovering the laws by which it is governed should be central to the study of political economy. In Ricardo's view—a view which would later influence Marx—the distribution of national income should be seen as being divided among the factors of production in the form of rent (paid to landowners), wages[4] (paid to labor), and profits (paid to capital). (Ferguson & Nell, 1972, p. 437); (Atkinson 1975, p. 2, 161); (Kaldor, 1955, p. 83) While the personal distribution of income received less attention, it was understood that economic returns would go to the owners of the factors of production, namely landlords, workers, and capitalists. (Atkinson 1997, pp. 297-298, 304); (Kaldor ,1955, pp. 83-88) The Ricardian theory, also referred to as the functional distribution of income theory, would later influence authors such as Pigou and the early Keynesians, including Kalecki and Kaldor. (Sahota, 1978, 22); (Kregel, 1979, pp. 51-53) It has also continued to influence the Neoclassical and Post-Keynesian theorists of today. (Atkinson, 1997, p. 304)

[4] The term wages, as opposed to earnings, typically refers to hourly-based pay only; while earnings is a broader term, referring also to professional salaries, including bonus payments and even stock and stock option grants. This usage will be followed in this study.

Ability Theory

While the Ricardian theory began with the factor distribution of income, which then led to the personal distribution of income, another early theory began at the level of the individual. This was *Ability* theory. Ability theory suggested that the personal distribution of income was a direct result of the distribution of abilities among a population.[5] An early work of this type was Galton (1869). Moreover, to the extent that ability was normally distributed—as was generally believed—income must be as well. This initial inference about the income distribution, however, was directly contradicted by the empirical work of Pareto (1897), who found that income was distributed log-normally, with a positive skew and a right-side tail. The discrepancy between the distribution of ability versus income led to the exploration of other factors—either in connection with ability or independently of it—that could help explain the non-normality of the income distribution. (Sahota,1978, 3-4); (Atkinson, 1975, pp. 78, 88); (Mincer, 1958, 281-282)

One explanation offered was that the abilities specifically relevant to obtaining income were not normally distributed. Another explanation offered was that there were different types of ability which—while they might each individually be normally distributed—interacted in a multiplicative fashion which resulted in a non-normal distribution of income. (Atkinson 1975, 89); (Sahota, 1978, 4) Some authors also incorporated a role for chance or luck in determining the nature of the income distribution. (Mincer, 1958,

[5] Abilities included both mental (intelligence) and physical (strength) traits.

282-283) Finally, Pigou suggested that the unequal distribution of property was to blame for the positive skew in the distribution of income. (Sahota, 1978, 3); (Mincer, 1958, 282); (Atkinson, 1975, 89); (Becker, 1975, 85)

Human Capital Theory

To many authors, ability theory—in its many iterations—as well as the alternatives offered, did not provide a convincing explanation for income inequality.   Some authors—such as Mincer (1958) —were particularly dissatisfied with the fact that most of these explanations failed to provide a role for strictly economic forces in determining the personal distribution of income.   (Mincer, 1958, p. 283); (Becker, 1975, 85-86) One body of theory which attempted to address this issue, and which would become influential within economics—as well as other social sciences—was *human capital theory*.

In discussions of the origins of human capital theory, reference is typically made to Adam Smith who articulated the idea that *wages* would fluctuate based on the cost—through education and training—of learning how to do a particular job. This occurred because occupations requiring longer periods of training would have to offer higher wages to attract workers. This simple idea—which in fact was more a theory of wages or earnings, rather than total income—became a thread that ran through the later development of human capital theory generally, and was particularly important in the application of human capital theory to the question of income inequality. (Sahota, 1978, p. 11); (Atkinson 1975, 79-80)

In the development of human capital theory, the term ‘human capital’ itself, while it could potentially apply to a great many types of investments of money or time—came to focus on education and training. (Sahota, 1978, p. 12) (Sweetland, 1996, p. 341) (Mincer 1958, p. 284) (Atkinson, 1975, p. 80) Investments in education or training, moreover, were treated within the *capital theory* framework. A gain in earnings achieved with a certain amount of time spent in training or education was considered a ‘return on investment.’ This gain in earnings could be expressed in terms of the percentage increase in earnings over what would have been the level without the investment. This percent was the “education premium.” The gain in earnings could also be defined in terms of the ratio between the gain and the cost of the investment. This was the rate of return. (Mincer 1991, p. 1)

Two early and influential figures in the formal development of human capital theory, and who specifically applied human capital theory to explain the distribution of earnings, were Mincer (1958) and Becker (1964).[6] Mincer (1958) sought to apply the economic theory of rational choice to help explain the dynamics of the earnings distribution. In Mincer’s view, the existence of rational choice meant that the earnings differences that

[6] The 2nd edition of Becker’s work, which was published in 1975, is the edition used as the reference for this study.

exist among individuals had to represent differences in the *costs* of obtaining a given level of income. The higher the cost associated with a given level of income, the higher the reward—in the form of wages—required to compensate for that cost. While the general cost of obtaining a given level of earnings might be represented by a number of things, such as investments in health and nutrition, Mincer focused on the costs of education and training.

To test his theory regarding the association between the level of earnings and the costs of education and training, Mincer developed a theoretical model, where the cost of training for an occupation was defined in terms of the length of time spent in training. According to the model, earnings inequality between occupations was a function of the *absolute* differences in the lengths of training required to enter each occupation. According to the function, the absolute differences translated into percentage differences for earnings. Earnings inequality within occupations could be explained in the model if the definition of training was expanded to include on-the-job experience. In such a model, the length of experience—measured by worker age—was rewarded with higher earnings. The rate at which earnings increased depended on the amount of training required to enter a given occupation: the more training required, the higher the rate of increase in earnings. (Mincer, 1958, 301)

In Becker (1964), the author developed a human capital model which suggested there was a relationship between ability, investments in human capital, and earnings. In his view, the individual level of ability was positively correlated with the *amount* of investment made in human capital. That is to say, the higher the level of individual ability, the larger the individual investment in human capital, and consequently, the higher the level of earnings. The correlation between ability and investments in human capital was derived from a basic principle in capital theory, which posits that the amount invested is a function of the expected 'rate of return.' In Becker's view, the level of ability essentially functioned as the 'rate of return' on investments in human capital.

Becker argued that the relationship between ability and the amount of investment in human capital had important implications for understanding the personal distribution of earnings. If the distribution of ability and investment were both symmetrically distributed and statistically independent of each other, the product of the two distributions would result in a slightly-skewed distribution of earnings. If the level of ability and investment in human capital were positively correlated, however, the product of these two symmetrical distributions could result in a significantly-skewed distribution. The extent of the skewness, moreover, would depend on the degree of correlation between the level of ability and the investment in human capital. (Becker, 1975, 83-87)

Studies using the human capital model to interpret earnings inequality continued into the 1970s—Mincer (1974) and Schultz (1975)—and the 1980s—Hause (1980) and Dooley and Gottschalk (1984). By the late 1980s, however, studies on income and earnings inequality began using the *labor market*, rather than the capital market, as a model to interpret changes in earnings inequality. An early example is Blackburn and Bloom (1987). A discussion of the labor market theory of earnings inequality will be presented in a later section.

Simon Kuznets

While ability and human capital theory used microeconomic principles to explain income inequality, there were alternative theories offered which viewed income inequality as a macroeconomic phenomenon. One influential example was the work of Simon Kuznets who, in his 1955 paper *Economic Growth and Income Inequality,* suggested that changes in income inequality in developed countries should be seen as being part of a broader process of macroeconomic growth and industrialization. (Kuznets, 1955, pp. 1, 3, 20) Kuznets developed his theory based on empirical evidence that in the United States, England, and Germany, income inequality had been falling since at least the 1920s, and possibly even since before WWI.

In Kuznets' view, during the early stages of industrialization and urbanization, when a country is beginning to see its agricultural sector decline and its industrial sector grow, inequality initially rises. This occurs as the rapid emergence of new industries gives rise to the creation of new fortunes in the industrial sector, which means that the relative incomes of top-income groups rise. At the same time, the relative incomes of low-income groups in urban areas fall due to declining death rates, rising birth rates, and the fact that "the emergence of the new industrial system had shattering effects on long-established pre-industrial economic and social institutions." (Kuznets, 1955, p. 18) The destruction of these older institutions, moreover, had a particularly negative impact on the incomes of low-income groups.

As the process of industrialization matured and broadened, however, income inequality would eventually reverse direction and begin to fall. The drop in inequality occurred due to the growth of the relative incomes of low-income groups, which itself occurred for a number of reasons. First, as the native born population in urban areas grew over time, workers would eventually be in a better position both to organize and adapt to the new environment, which allowed them to obtain greater incomes. In addition, once workers were more established, they would experience an increase in efficiency, and presumably, income. Finally, low income groups also benefited from the supporting social legislation which inevitably came in democratic societies which had industrialized and urbanized. (p. 17)

Kuznet's theory regarding the changing direction of income inequality over time would later be represented graphically by an inverted U, with inequality plotted on the vertical axis and total national or per capita income plotted on the horizontal access. See Figure 3 on the next page. At lower levels of national income, where countries are just beginning to industrialize, inequality grows alongside growing national income over time. At higher levels of national income, however, where countries have more fully industrialized, inequality begins to fall as national income grows over time.

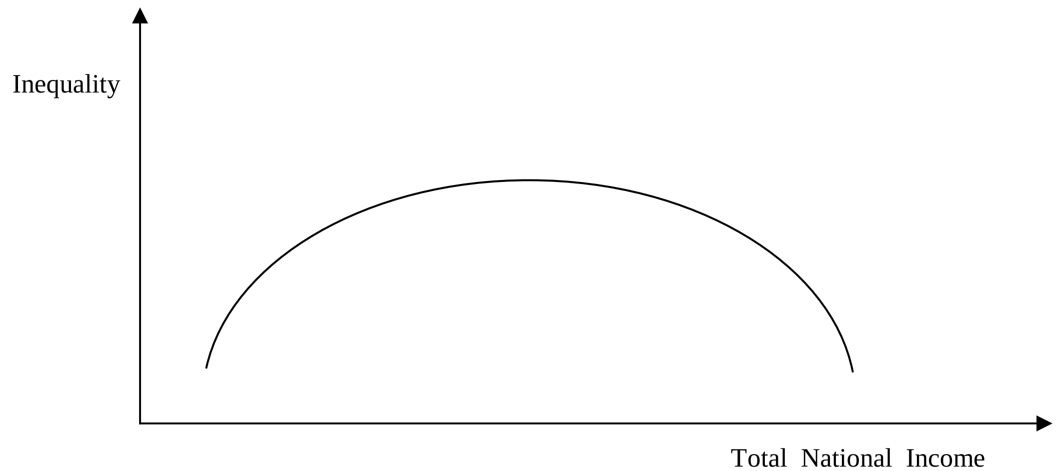

Figure 3: The Kuznets Curve

The Kuznets hypothesis would prove to be an influential theory of income inequality, particularly in the early post-WWII era. (Conceicao and Galbraith, 2001a, p. 148) Interest waned in succeeding years, however, as did interest in the study of income inequality generally. Since the renewal of interest in the topic in the 1980s, however, the Kuznets curve has, to some extent, re-emerged in the literature; although it is not typically included in mainstream economic discussion. Some examples of more recent references to Kuznets include Harrison, Tilly, and Bluestone (1986), and more prominently Atkinson (1997) and Galbraith (2001) and (2012). There are also a number of references to Kuznets in the regional science literature; with examples including: Chakravorty (1996b), Nielsen and Alderson (1997), and Yorukoglu (2002). The regional science literature on income inequality will be discussed in a later section on the spatial dynamics of earnings inequality.

The Business Cycle and Inequality

In Kuznets (1955), the author had described changes in income inequality as a "secular" or long-term phenomenon, where changes occurred independently of business cycles. However, in an earlier paper—Kuznets (1953)—the author had also suggested that changes in income inequality could be analyzed as a short-term phenomenon, where the short-term was defined by the movements of the business cycle and the associated changes in production and employment. In this earlier work, Kuznets calculated the shares of national income going to individuals in the top 5 percent[7] of the income distribution for a number of years during the interwar period (1919-1939). He found some evidence that the shares of the top 5 percent moved in a counter-cyclical fashion: falling during economic expansions and rising during recessions. This suggested that income inequality in the entire population was counter-cyclical as well. Kuznets offered no explanation—speculative or otherwise—as to why income inequality might be anti-cyclical, noting that doing so was not possible given the narrow scope of his data.

Research examining the relationship between income inequality and the business cycle was also conducted in the 1960s and 1970s. Some examples include Metcalf (1969) and Blank (1988). Metcalf (1969) examined changes in the distribution of income among families for the period 1949-1965. He found that during periods of economic expansion, the relative position of low income families—whose chief income came from wages—

[7] Data for other segments of the income distribution were not readily available.

improved, while the relative position of upper income families fell. (p. 667) He found this effect was less pronounced for families headed by females than it was for families headed by males. In Blank (1988), the author used sample data for the years 1969 to 1981 to examine how macroeconomic conditions affected income and employment for households in a variety of demographic groups. She found that income inequality overall fell during economic expansions. This was due to the fact that wage incomes for low-income groups grew very strongly during expansions, more strongly in fact than other income groups. The growth in low-wage incomes, moreover, was driven by an increase in both hourly wage rates and total hours worked.

While some degree of consensus had thus been established by the early 1980s that economic expansions were associated with falling income inequality—and recessions were associated with rising inequality—this consensus began to erode once researchers started to examine inequality data for the 1980s. A number of researchers were in fact finding that even during the post-1982 economic expansion, income inequality in the U.S. was continuing to grow. (Parker, 1998, p. 206); (Levy and Murnane, 1992, 1351); (Galbraith. 1998, 23-24); (Danziger and Gottschalk, 1995, p. 135) This finding led to declining interest in the role of the business cycle in explaining income inequality, helping to prompt the search for alternative explanations.

The 1980s: Deindustrialization and the Loss of Middle Class Jobs

It was during the 1980s that more extensive empirical work on income and earnings inequality in the U.S. began. The relative lack of interest before then has been attributed to the belief that income inequality had been stable or falling during the first three decades after WWII. By the early 1980s, however, there was a growing sense that income, and more specifically, earnings inequality in the U.S. had begun to rise. Levy and Murnane (1992) provide a good account of how the early studies of earnings inequality emerged in the early 1980s and continued thereafter. The first of these studies included some popular publications, including Barry Bluestone and Harrison Bennett's book, *The Deindustrialization of America*, published in 1982, and an article by Robert Kuttner in *The Atlantic Monthly* entitled 'The Declining Middle,' published in 1983. These works argued that in the 1970s, the U.S. economy had begun a process of "deindustrialization," or a decline in its manufacturing base, and the loss of a substantial number of middle-income jobs. These manufacturing jobs, moreover, were largely being replaced by employment in the high-technology industry—where earnings tended to be relatively high—and in the retail trade and services sectors—where earnings tended to be relatively low. (Bluestone & Bennett, 1982, p. 95-97); (Kuttner, 1983, p. 62) The inevitable result of the concentration of employment at the top and bottom of the wage distribution, moreover, was growing earnings inequality.

As these and other works began to focus popular attention on the issue of the loss of middle-class jobs and the related issue of earnings inequality, more academic studies soon followed. Lawrence (1984) found that between 1969 and 1983, the proportion of full-time *male* workers earning a middle-class wage had shrunk from 56 percent to 47 percent. (Levy and Murnane 1992, 1347) Subsequently, Bluestone and Harrison (1986) found that, compared to the period 1973-1979, the net new employment created between 1979 and 1984 had occurred disproportionately at the low end of the wage distribution. This result was based on the annual earnings of all workers, not just full-time, as was the case in the earlier work of Lawrence. In response to the work of Bluestone and Harrison (1986), Kosters and Ross (1987, 1988) would argue that their findings were a result of comparing 1979, a business cycle peak, to 1984, an early part of a recovery. Moreover, by extending the analysis to 1985 and utilizing a different methodology, Koster and Ross found that there had *not* in fact been a disproportionate growth of jobs for all workers at the low end of the wage distribution over the 1979 to 1985 period. However, when Kosters and Ross applied their methodology to include year-round, full-time *male* workers, they found that this group's middle-class was indeed shrinking. This finding was consistent with the earlier findings of Lawrence (1984). (Levy and Murnane ,1992, 1349)

In addition to the middle-class articles in the 1980s, studies were also being conducted which sought to directly measure the evolution of earnings inequality in the U.S. in the 1970s and 1980s. Moreover, if the middle of the earnings distribution for men was indeed hollowing out, this fact should be reflected in a rise in earnings inequality. Henle and Ryscavage (1980) examined the evolution of earnings inequality among men for the 1958 to 1977 period. In terms of their methodology, they calculated Gini coefficients using annual earnings data from the Current Population Survey (CPS) of the U.S. Census. They found that for all male earners—including part-time and part-year workers and the self-employed—inequality grew steadily from 1968 to 1977. The authors noted, however, that when they limited their population to full-time, year-round workers only, they found little or only very moderate growth in inequality over these years. Subsequently, Dooley and Gottschalk (1984) also utilized earnings data from the CPS to calculate measures of inequality for the years 1967 to 1978. Their population sample also was male workers and included part-time and part-year workers, though they excluded the self-employed. As their inequality measure they used the variance of log earnings. They found that earnings inequality grew steadily over the 1968 to 1977 period.

By contrast, Harrison, Tilly, and Bluestone (1986) calculated measures of earnings inequality among all workers, including both part-time and full-time and male and female, for the period 1969 to 1983, and found that inequality had *fallen* for most of the 1970s and begun growing only after 1978. In addition, Blackburn and Bloom (1987) calculated measures of earnings inequality for the period 1967 to 1985 and found that there had been little trend over this period at all. They did, however, find that inequality of total family incomes had steadily grown over these years.

One explanation for these conflicting findings has been provided by Karoly (1992), who applied ten different inequality measures to CPS wage and salary data for the years 1967 to 1986 and compared the results. The author also calculated measures separately for men and women. Karoly found that there were differences in the direction, timing, and degree of changes in inequality depending on the measure utilized. For example, while eight of the ten measures showed a significant growth in inequality from 1979 to 1986, the Gini coefficient and the relative mean deviation measures showed only a very modest increase over these years.[8] This helps to explain the findings of Blackburn and Bloom (1987). In addition, Karoly found that the changes in inequality were different for men versus women. For men, inequality had grown—albeit very moderately—during the 1970s, while inequality for women had fallen. Moreover, the decrease in earnings inequality among women had contributed to the fall in inequality among all workers during the 1970s. This reconciles the findings of Henle and Ryscavage (1980) and Dooley and Gottschalk (1984), with those of Harrison, Tilly, and Bluestone (1986). Karoly's own conclusions about the pattern of wage inequality over the 1967 to 1986 period was that inequality was stable or falling during the 1970s, but had steadily grown over the period from 1980 to 1986.

[8] This might have to do with the fact that the Gini coefficient is most sensitive to transfers at the mode of the distribution while the relative mean deviation is insensitive to transfers on the same side of the mean.

Institutionalism and Earnings Inequality

While the deindustrialization hypothesis proved to be an influential theory of earnings inequality, and had initially helped spawn the empirical work of the 1980s, there were alternative explanations being presented in the literature. One group of explanations comes from the Institutional School of economics. Moreover, Institutional explanations for earnings inequality have consistently appeared in the literature—and continue to do so—even as the mainstream debate has tended to focus on other causes.

Institutional economics is a remarkably broad field with a long history in American economic thought. While the work of the early Insitutionalists, such as Thorstein Veblen, John R. Commons, and Clarence Ayres touched on the issue of income inequality, it did not provide a coherent or consistent theory of the phenomenon. The renewed interest in the topic of inequality since the 1980s has lead to the identification of specific institutions as being important sources of income inequality. Among these include the falling real value of the minimum wage and the decline in union membership and union power. Between 1981 and April 1990, for example, the nominal minimum wage in the U.S. was fixed at $3.35 per hour, while inflation decreased in real terms by 44 percent. This could be at least partially responsible for falling real wages for those at the bottom of the wage structure. Unions may also play an important factor, as they tend to decrease inequality in firms by reallocating some of the payroll to lower-income workers. Unions also work to bring workers' wages closer to the overall average in the wage structure. The proportion of the workforce that is unionized has in fact been falling rapidly since 1975 in the U.S., when the unionization rate was at about 29 percent. By 1991, this figure had dropped to about 18 percent. (Danziger and Gottschalk, 1995, 128-130)

Another possible explanation posed by the Institutionalists regarding inequality, and more specifically, income inequality, has to do with the tax structure. A significant shift of the tax burden from one income group to another over time could cause an increase in overall income inequality. According to the Economic Policy Institute (EPI) in Washington, D.C., a sharp reduction in effective federal tax rates for the richest 1% of taxpayers in the U.S. has contributed to a rise in income inequality since 1979. This tax cut has occurred while the effective tax rate for a middle-class family of four has changed little since 1980. (Mishel et al, 1998, p. 4) Similarly, a study by the Congressional Budget Office on income and tax trends since 1979 in the U.S. found that the percentage of income that Americans pay in federal taxes declined between 1979 and 2001 among every income group, but that households in the top 1 percent of the income distribution had the largest percentage-point fall in effective tax rates. (CBO, 2001)

While Institutionalists point to a variety of institutions as being important sources of inequality, it is fair to say that many provide a role for *power* in deciding the distribution of economic benefits in society. In other words, economic activity is social in nature. In conditions of scarcity, the struggle for power can be seen as occurring between employer and employee, landlord and tenant, and, one might add, finance capital and the business firm. (Brown, 2005, 919-920) One of the more influential American economists from the Institutionalist school has been John Kenneth Galbraith, who has written extensively on the role of power in the economic system. Regarding income inequality Galbraith (2004) has argued that an important development in recent years has been the transition of control over corporations from stockholders (the owners of capital), to executive managers. (Galbraith, 2004, pp. x, 3) With effective control over the corporation, executives have been able to set their own pay, choosing to increase it significantly through growing salaries, bonuses, and stock options. (Galbraith, 2004, 18-19) One of the results has been a steady increase in pay inequality within corporations between executives and average workers. Indeed, Piketty and Saez (2003) have offered evidence that the dispersion in pay between corporate executives and their average employees has been growing since the mid-1970s. (p. 33)

Another Institutionalist explanation for rising income inequality comes from economist Hyman Minsky. Minsky argues that the rise of income and wage inequality in the U.S. is in part the result of the evolution of its financial structure. In the current era, institutional investors dominate financial markets and transactions, and by extension, the real economy. In Minksy's words, we live in the age of "money-manager" capitalism. Under this system, the money managers who work for the large pension and mutual funds focus above all else on maximizing the value of their fund assets. In doing so, they have placed great pressure on business leaders to concentrate on short-term profits and the stock-market valuation of their firm. This has promoted, among other things, the practice of continually downsizing and laying off employees to keep costs down and equity values up. In other words, profits have come to be concentrated in financial assets, versus being paid out in salaries and wages. This, in turn, has meant decreases in average wage levels for workers, growing capital incomes, and the consequent rise in income inequality. (Minsky and Whalen, 1996, pp. 156, 159)

Neoclassical Theory and the Dual Labor Market Thesis

As the studies of earnings inequality proliferated in the 1980s and into the early 1990s, the mainstream consensus about its causes continued to evolve. In the earlier work of Bluestone and Harrison (1982), the authors had originally made the influential argument that growing earnings inequality was caused by the process of deindustrialization; or the decline of mid-wage manufacturing activity and the growth of low-wage service activity. But critiques of the deindustrialization hypothesis would emerge, which included the argument that Bluestone and Harrison had not taken into account some of the demographic changes that had occurred among the workforce in the 1980s. More importantly, a number of papers, such as Lawrence (1984) and Grubb and Wilson (1989), were finding that the growth of earnings inequality in the 1980s was occurring *within* manufacturing and service industries as well as *between* them. (Levy and Murnane, 1992, 1347-1352) This meant that sectoral changes in the economy alone could not fully account for the growth of earnings inequality. (Levy and Murnane, 1992, 1351), (Galbraith, 1998, 23-24)

Given the perceived weaknesses of the deindustrialization hypothesis, by the early 1990s, a new consensus about the causes of growing earnings inequality began to emerge. This new consensus in many ways built upon the earlier human capital theory, simply replacing the *capital market* with the *labor market* as the framework to interpret changes in earnings inequality. In the work of Levy and Murnane (1992), Katz and Murphy (1992), Bound and Johnson (1992), Juhn, Murphy, and Pierce (1993), and Wood (1994), the authors would argue that the growth of earnings inequality in the 1980s could be explained via the neoclassical labor market, with the market redefined in terms of two types of labor: *skilled and unskilled.*[9] Skilled workers generally received higher wages than the unskilled because they benefited from an education or skill premium.[10] Moreover, *changes* in the degree of inequality of wages between skilled and unskilled workers were the result of shifts in the demand and/or supply of one type of labor relative to the other.

According to the articles from the early 1990s, the most important causes of growing earnings inequality in the 1980s originated from changes on the demand side of the labor market. Of these, the most important was an increase in the demand for skill due to 'skill-biased technological change.' Skill-biased technological change (SBTC)—which was a byproduct of the computer revolution and the widespread adoption of information

[9] Skill is typically represented and measured by years of education or amount of on-the-job experience.
[10] The education premium concept goes back to human capital theory, covered earlier.

technologies—increased the premium enjoyed by skilled workers in the labor market, causing their earnings to rise relative to the unskilled, and earnings inequality to grow. The early 1990s articles also suggested that while a similar increase in the demand for skilled labor had occurred in the U.S. in the 1970s, its positive effect on the relative wages of skilled workers had been counteracted by the simultaneous increase in the *supply* of skilled labor. Moreover, this increase in the supply of skilled labor was a result of the entry of the well-educated baby-boom generation into the labor market.

Another demand-side change which had caused earnings inequality to grow in the 1980s—and about which there was less consensus than SBTC—was a *decrease* in the demand for *unskilled* labor, due to an increase in international trade.[11] Specifically, an increase in the trade of manufactured goods between the U.S. and developing countries had caused a weakening of the manufacturing industry in the U.S. Moreover, because the manufacturing industry tends to utilize unskilled labor, its decline caused a reduction in demand for unskilled labor. The decline in demand for unskilled labor, in turn, caused the relative earnings of these workers to fall and earnings inequality to grow.

In the wake of the early articles on the dual labor market thesis, research in this area continued. In the work of Danziger and Gottschalk (1995) and Topel (1997), the authors—in addition to discussing demand-side factors—described some of the supply-side factors that theoretically could have contributed to growing earnings inequality in the

[11] This is the argument most identified with Wood (1994).

U.S. in the 1970s and 1980s.[12] Examples of supply-side factors included immigration, female labor force participation, and labor cohort size. Growing rates of immigration and female labor force participation could have caused an increase in the supply of unskilled workers in the labor market, depressing their earnings. This is because both groups were less likely to have completed high school or college. Similarly, the entrance of the large baby-boom population into the workforce in the 1970s may have led to a large increase in the number of young (unskilled) workers entering the workforce during that decade. This too could have depressed the wages of the unskilled.[13] Based on their surveys of some of the relevant literature, Danziger and Gottschalk (1995) found that there was, in fact, some evidence that immigration played a role in the growth of earnings inequality in the 1980s, while Topel (1997) concluded that the impact of immigration was minimal. In terms of female labor force participation, Topel generally found the evidence to be inconclusive. Regarding labor cohort size, both Danziger and Gottschalk and Topel concluded there was evidence of a role for labor cohort size in the growth of earnings inequality, particularly during the 1970s.

In the 2000s and up to the present time, the dual labor market thesis has continued to be the general framework used by most mainstream economists to analyze and interpret changes in earnings inequality in the U.S. Moreover, within this framework, the demand-

[12] While the early 1990s articles had focused on the growth of earnings inequality in the 1980s, suggesting that it had not grown much (if at all) in the 1970s, there is a fair amount of research—such as Danziger and Gottschalk (1995) and Topel (1997)—which finds that earnings inequality had grown in the 1970s as well.
[13] It is interesting—and somewhat puzzling—to note that this is the exact opposite of the effect of the entry of the baby-boom generation into the labor market in the 1970s suggested by Katz and Murphy (1992).

side effects of SBTC and international trade continue to be the most commonly-cited explanations for the growth of earnings inequality. For example, Acemoglu (2002) reaches the general conclusion that SBTC was the most important cause of growing earnings inequality in the U.S. in the 1970s, 1980s, and 1990s. In Autor, Levy, and Murnane (2003), the authors—noting the significant evidence for the existence of SBTC—seek to examine more specifically how and why the adoption of computers and information technologies led to an increase in the demand for skilled workers in the U.S. Responding to a critique of SBTC by Card and DiNardo (2002), Autor, Katz, and Kearny (2008) concluded that increases in the demand for skill played a primary role in the growth of earnings inequality during the 1980s and from 1990 to 2005. Moreover, the increase in demand for skill was due to skill-biased technological change.

Racial and Gender Discrimination and Earnings Inequality

As has just been seen, the impact of changing workforce demographics on earnings inequality can be interpreted via the dual labor market thesis, where different demographic groups are paid according to their level of skill. Regardless of the theoretical model used to explain *why* earnings inequality exists between different demographic groups, it is reasonable to assume that an increase over time in the labor force participation rates of low-earnings groups such as women, African-Americans, and Hispanics *could* lead to an increase in earnings inequality for the working population overall. This is because the median earnings levels of these groups—while they may have gained on white men—continue to be consistently lower than the population median.[14] It is certainly true, moreover, that the workforce participation rates of women and certain minorities have increased significantly in the U.S. For example, the labor force participation rates for women increased from 43.3 percent in 1970, to 59.8 percent in 1998; while the rate for African-Americans increased from 61.0 percent in 1980 to 65.6 percent in 1998; and the rate for Hispanics increased from 64.0 percent in 1980 to 67.9 percent in 1998. (Fullerton, December 1999)

An alternative to the dual labor market thesis explanation for the low level of earnings that prevail for women, African-Americans, and Hispanics is *racial and gender discrimination;* specifically at the point of hiring and in salary and promotion decisions. While it is certainly true that the economic and sociological literature has increasingly focused on other explanations for earnings inequality, there continues to be interest in the role of racial and gender bias.[15] For example, in Blau and Kahn (1994), the authors examine the drop in the male-female pay gap which occurred amidst the increase in earnings inequality in the population overall. They found that improvements in women's occupations and levels of experience, as well as the smaller negative effects of de-unionization on pay levels—compared to men—all contributed to a narrowing of the

[14] Whether or not an increase in the labor force participation rates of these groups would lead to an increase in earnings inequality for the working population overall would depend on the rate of growth of their participation rates *relative* to the rate of growth of their median earnings. In general, if their relative median earnings are growing at a faster rate than their labor force participation rate, then this would cause—all else equal—earnings inequality for the population overall to fall. If the reverse were true, then—all else equal—earnings inequality in the population overall would increase.

[15] The decrease in interest may simply reflect the belief that race and gender generally contribute far less to earnings inequality today than they did in the past. (Schweitzer, 1997, p. 22)

male-female pay gap . The authors also found a decrease in the unexplained portion of the male-female pay gap, which they attribute to either an improvement in women's unmeasured skill level or a decrease in *discrimination.*   (p. 31) Roscigno, Garcia, and Bobbitt-Zeher (2007) note that racial and gender inequalities in the labor market persist even when controlling for levels of human capital (skill). Part of the reason for this, they conclude, is contemporary discrimination in the form of social closure. Social closure refers to the processes by which social collectives restrict access to their group and its associated privileges. (p. 21)

Studies of Earnings Inequality in the 1990s and 2000s

As was seen previously, there were some conflicting findings regarding whether earnings inequality had actually grown in the U.S. in the 1970s and 1980s. By the early 1990s, while there continued to be little consensus about the 1970s, there was general agreement that earnings inequality had grown in the 1980s. (Levy and Murnane, 1992, p. 1371) It is certainly true that—as previously illustrated by Karoly (1992)—the results of research on income and wage inequality can be highly sensitive to the choice of inequality measure utilized, the specific years covered, and the population studied. In addition, it has become clear in recent years that the *source* of earnings data can also affect results. For these reasons, there continues to be some conflicting findings regarding the evolution of earnings inequality in the U.S. in the 1990s and 2000s. For example, Card and DiNardo (2002) find, based on data from the March CPS, that while wage inequality had grown significantly in the 1980s, its growth stabilized in the 1990s. (p. 748) At the same time, the U.S. Census Bureau has calculated measures of earnings inequality for the years 1967 to 2005. They have found that the broad trend has been for individual earnings inequality to continue growing in the 1990s and the 2000s, although at a slower rate than in the 1980s. (U.S. Census, 2007)

One of the important methodological issues involved in the study of earnings inequality concerns the problem of "top-coding" in data from the March CPS, which is the most commonly used data source in inequality studies. The top-coding problem stems from the fact that annual earnings data for individuals above a certain amount is censored in the publicly-available data from the March CPS. From 1968 to 1981, annual earnings data were censored for anything above $50,000; from 1982 to 1984, data were capped at $75,000; and in 1984, the cap was raised to $99,000. After 1989, the top-coding problem became more complicated as individuals who had more than one job could report their earnings from each separately, and each was censored separately. (Bernstein and Mishel, 1997, 3-4), (Card and DiNardo 2002, 744), (U.S. CBO, 2001, 59), (Lerman, 1997)

The issue of top-coding becomes particularly important for research on earnings inequality if there are important changes occurring at the top of earnings distribution. Indeed, Atkinson (2007) has found that the most significant change in the earnings distribution over the last 25 years in the U.S. has been the relative rise in the top decile, which has risen by more than 15 percent. (p. 50) For this reason, Atkinson has argued that research in the U.S. should be focused on changes at the top of the distribution. (p.

42) Additionally, Card and DiNardo (2002) have noted in their research that when data are adjusted for top-coding, they find that wage inequality grew by about 5% in the 1990s. (p. 748) The importance of the top-coding problem has also been noted by Katz and Autor (1999), who have argued that their measures of earnings inequality would have expanded more dramatically generally if they included data from the top 1% of the income distribution. (p. 1468)

Some recent research has, in fact, addressed the top-coding problem by utilizing individual tax return data from the IRS. This work has demonstrated that very significant changes have indeed occurred at the top of the earnings distribution in the U.S. For example, as already partially seen in the Introductory chapter, in the work of Piketty and Saez (2003) and (2006), the authors examine changes at the top of the income and earnings distribution in the U.S. extending back to 1927. As illustrated in Figure 4, the authors found that the proportion of total income and earnings going to individuals in the top 10 percent of the income distribution was very stable in the post WWII era—having dropped precipitously during the war—and then began growing steadily in the early 1970s. In fact, the share of total earnings going to the top decile increased from 25.7 percent in 1970 to 35.8 percent in 2006. (Piketty and Saez 2003 and 2006)[16]

[16] As noted in the Introduction, the jump in measured inequality for income and earnings from 1986 to 1988 is at least in part due to the Tax Reform Act of 1986.

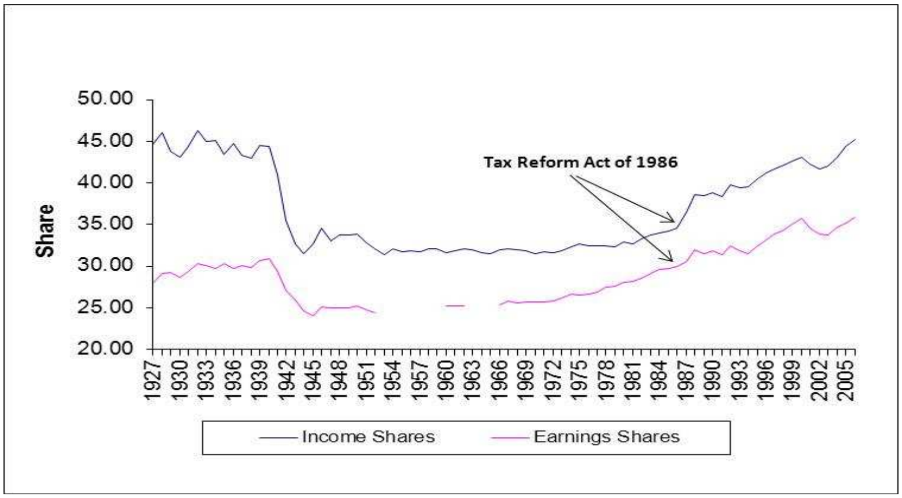

Figure 4: Top Decile Shares of Total National Income and Earnings, 1927 – 2006

Source: Piketty and Saez[17]

In addition to the work of Piketty and Saez, the U.S. Congressional Budget Office (CBO) (2001) and (2006) has also used data from the IRS, in combination with Census data, to construct measures of income inequality for the 1979 to 2005 period. CBO found that during these years average after-tax household incomes grew at highly unequal rates in the U.S. among the different quintiles of the income distribution. The average incomes of households in the highest quintile grew by about 69% over this period, while average incomes for households in the lowest quintile grew by about 6%. Moreover, due to the fact that the average incomes of households at the highest quintile grew so rapidly, this group's share of total income grew from 42.4% to 50% over this period. The change in

[17] http://emlab.berkeley.edu/users/saez/, downloaded January 2009.

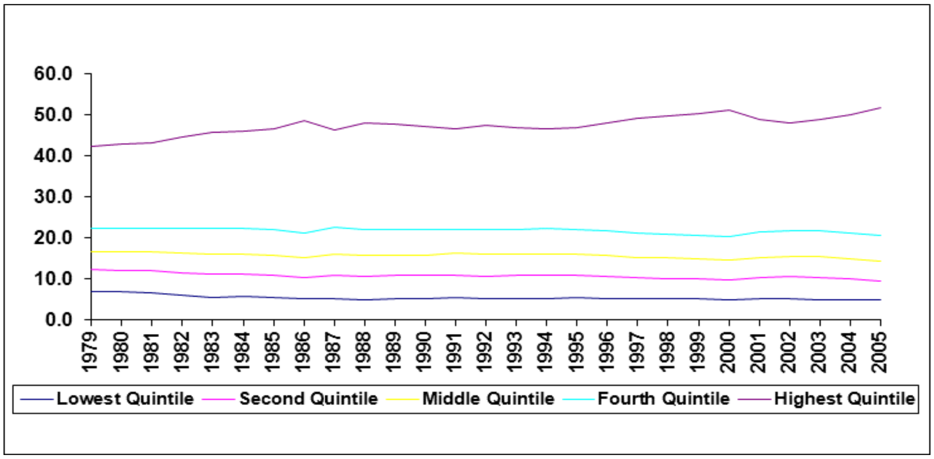

Figure 5: Shares of After-Tax Income by Quintile, 1979 to 2005

Source: CBO

shares for each quintile is illustrated in Figure 5.[18] The appeal of the CBO data is that in addition to representing after-tax income, they are comprehensive, and include: wages, salaries, self-employment income, rents, interest, dividends, realized capital gains, cash transfer payments, retirement benefits, and in-kind benefits. (p. 13)

One of the implications of the work of Piketty and Saez and the CBO is that many of the previous studies which relied on data from the CPS of the U.S. Census Bureau have—due to the top-coding problem—generally underestimated the growth of income and earnings inequality in the U.S. Based on the work of Piketty and Saez and the CBO, moreover, it might be concluded that earnings and income inequality did grow in the 1990s, and not

[18] It is worth noting that much of the increase in the share of the top quintile is driven by increases in the incomes of households in the top 0.5% of the income distribution.

just in the 1980s, as argued by Card and DiNardo (2002). The evidence for the 1970s is weaker, however, as the CBO data do not cover this period, and the Piketty and Saez data show only a modest growth of the top decile over the decade. We should also note, moreover, that the work of Piketty and Saez and the CBO do not provide summary measures of income or earnings inequality for the distribution overall, and there are apparently few studies thus-far that have utilized data from the IRS to do so.

One exception to this is Galbraith and Hale (2006), who used income data based on tax returns from the U.S. Bureau of Economic Analysis' (BEA) Local Area Personal Income Statistics.[19] In their research, the authors utilize Theil's T Statistic to measure income inequality across all *counties* in the U.S. The authors find that income inequality fell through the first half of the 1970s, then began growing modestly around 1975 and accelerated through the entire decade of the 1980s. Inequality then fell to some degree from 1990 to 1995, but then began to grow strongly again until 2001, after which it declined sharply until 2003. Since 2003, income inequality has begun to grow again. Indeed, the work of Galbraith and Hale does generally match the work of the CBO and Piketty and Saez for the 1980s, 1990s, and 2000s. We should note, however, that Galbraith and Hale and the CBO use personal income data, whereas Piketty and Saez just use earnings. However, the fact that their results are very similar suggests that earnings inequality is a major factor in the growth of overall income inequality in the U.S.

[19] **Personal income** in the BEA data includes earnings, rental income, dividend income, interest income, and transfers.

The Spatial Dynamics of Income and Earnings Inequality in the U.S.

As mentioned in the introductory chapter, a great deal of research has been done examining income and earnings inequality at the national level in the U.S., but less work has been done examining its spatial dynamics. There are, in fact, a number of ways to explore the spatial dynamics of income inequality. For example, Langer (1999) and Bernstein, et al (2006) have looked at the income distribution *within* American states to observe how levels have varied across the nation. In addition, Madden (2000) and Hyclak (2000) have examined and compared income inequality levels within metropolitan and urban regions. Moreover, Galbraith and Hale (2004) have looked at how income inequality *between* counties in the U.S. has changed over time, while Nielsen and Alderson (1997) have examined the factors affecting income inequality *within* U.S. counties for the years 1970, 1980, and 1990. Much of this literature does indeed demonstrate that there is a significant spatial variation in the levels of income inequality in the U.S.

A great deal of the theoretical and empirical research on income inequality done at the metro or city level can be found in the regional science literature. This literature has traditionally focused on population size, density, and growth rates as the key determinants of income inequality within cities or metros. This focus reflects the early influence of Simon Kuznets, where city size and growth rates are seen as indicators of urbanization and the level of economic development. However, the influence of human capital, deindustrialization, and neoclassical theory is also clear in this literature, effectively linking it to the broader world of economic theories of income and earnings inequality.

For example, in Burns (1975) the author examines income inequality within metro regions in the US and the Netherlands during the 1950s, and applies both human capital and Kuznets' stages of growth theory to interpret the results. Included in his findings—which were similar for each country—was that metro areas with higher than average incomes had *lower levels of* income inequality. Here, average income was used as a measure of development. In addition, Burns found that cities with unequal distributions of years of schooling among their populations, a smaller manufacturing sector, a larger minority population, and slower rates of population growth, all had *higher* levels of inequality.

Following in the vein of Bluestone and Harrison (1982) and the deindustrialization hypothesis, Nelson and Lorence (1988) measured inequality for the largest 130 metro areas in the U.S. and examined the role of the service sector in earnings inequality. They found that service sector employment was positively correlated with earnings inequality, although the reasons differed for men and women. For men, a larger service sector leads to higher earnings inequality because of the existence of high-paid jobs in the business and professional services sectors. For women, services increase inequality because of the large number of low-paid jobs in retail trade and social services. Similarly, Beeson and Tannery (2004) examined the impact of the decline in employment in the steel industry on earnings inequality in the Pittsburgh metro area during 1980s. They found, in fact, that the shifts in employment out of the steel industry were largely responsible for the increase in earnings inequality in the 1980s.

Finally, Chakravorty (1996) analyzed income inequality in metro areas with a population above 250,000 based on 1990 US census data. He found that the key factors associated with inequality were the unemployment rate, family structure, and the distribution of education among the population. This result was quite different from what had been found in earlier decades—such as the 1950s and 1960s—where income inequality mostly depended on income level, industry mix, and racial composition.

Some of the more extensive empirical work measuring income and earnings inequality in metro areas in the U.S. in recent years includes the work of Madden (2000) and Hyclak (2000). For this reason, these studies deserve a closer review. Madden (2000) examined household income and individual earnings inequality in the 1980s in the 182 largest metropolitan statistical areas (MSAs) in the U.S. As a data source, the author used the 5 percent Public Use Micro Samples data from the 1980 and 1990 censuses, and for an inequality measure, the Gini coefficient. What Madden found was that, of the 182 largest MSAs in the U.S., just four saw a *decrease* in household income inequality in the 1980s, and just 26 saw a *decrease* in individual earnings inequality in the 1980s. All the rest saw some amount of increase in household and earnings inequality, though for some it was quite small. (168-178) Nevertheless, this broad pattern does offer evidence that, at least for the 1980s, the growth of income and earnings inequality at the national level in the U.S. was matched by some level of growth in the great majority of its largest metropolitan regions.

Hyclak (2000) examines earnings inequality in the 1980s within 20 large urban areas using data from the Area Wage Survey (AWS) of the U.S. Bureau of Labor Statistics (BLS). The AWS provides data on the hourly wages paid to workers in about 40 different jobs clustered in four occupational groups, including professional-technical, clerical, skilled maintenance and material movement, and security and janitorial. As a measure of inequality, the author used the variance of the natural logarithim. Hyclak found that earnings inequality increased significantly in all 20 urban areas during the 1980s. This finding accords well with that of Madden.

The Keynesian and Post-Keynesian Theories of Income and Earnings Inequality

By this point, much of the existing theoretical literature on income and earnings inequality has been discussed. There is, however, a body of theory not yet covered which, while outside the mainstream of economic thought, offers a compelling and coherent explanation for income and earnings inequality. This is Post-Keynesian theory, which was born in the wake of the Keynesian revolution of the 1930s, but emerged most significantly in the 1950s. This new economic school was developed by economists who sought to extend and improve upon the work of Keynes in a number of areas. (Eichner, 1979, p. 9) It is the Post-Keynesian theory, moreover, that provides the basis for the theoretical model to be explored and tested in this study, and thus a thorough review is necessary here.

Keynes himself dealt very little with the issue of the income distribution. Observers have noted that this is not surprising given that the most important economic issues of his day were the mass unemployment and poverty brought on by the Great Depression. (Galbraith, 2001a, p. 32); (Atkinson, 1975, p. 2) (Kaldor, 1955, p. 94) One of the few things Keynes did say about income inequality was that, in his view, the factor shares of national income had been remarkably stable over time. (Atkinson ,1975, pp. 24, 165) It was not until the later work of the Post-Keynesian school, therefore, that a strictly Keynesian theory of the income distribution would be developed.

The Post-Keynesian theory of income and earnings inequality began by returning to the Classical question of the division of national income between aggregate wages and aggregate profits; where aggregate wages go to workers and aggregate profits to capitalists. In the Post-Keynesian view, aggregate wages are determined by the total demand for consumption goods, whereas aggregate profits are determined by the total demand for capital—or investment—goods, plus luxury consumption. It is therefore the investment decisions of the capitalist class which, in addition to determining the level of total output in an economy, determine the national distribution of income. (Kregel, 1979, pp. 47, 52-53); (Galbraith, 2001b, pp. 7-8.)

Per this theory, the flow of investment and consumption demand, or the business cycle, is a key factor driving changes in the distribution. Investment demand, which generates high profits for the capitalist class, is typically highest at the beginning of an economic expansion. As an expansion proceeds, however, investment demand gives way to growing consumption demand and growing aggregate wages. At this point, capitalist profits weaken and new business spending falls, which, in turn, slows the economic expansion. Inequality in the national distribution of income, therefore, tends to increase during periods of economic slowdown and early recovery, when capitalist profits are highest, and decrease in the later stages of expansions, when consumption demand and wages are highest. (Galbraith, 2001b, 8.)

The distribution of aggregate wages *among workers*, however, is a separate issue which was not fully addressed by the early Post Keynesians. In recent years, the economist James Galbraith has sought to develop a post-Keynesian theory of the earnings distribution. In Galbraith's view, wage or earnings levels vary significantly *by industry*, and are determined by the prevailing market structures within which firms in different industries operate. Moreover, the wage levels in each industry respond differently to changing macroeconomic conditions. (Galbraith, 2001b, pp. 8-10.)

To illustrate this view, Galbraith utilizes a taxonomy which divides the economy into three sectors. The first sector is the *S sector*, S standing for services. This sector is similar to the large low-wage service sector and operates in a competitive market.

Because of competition, profits in this sector are generally low, as they represent a small mark-up over the costs of operations. Wages here also tend to be quite low, as workers have little leverage over their wages. The lack of leverage is due to the fact that workers here are low-skilled and can be easily replaced. High turnover will not have much of an effect on a firm's profits. (Galbraith, 2001a, p. 37); (Galbraith, 1998, p. 92)

The second sector is the *C sector*, C standing for consumption goods. (Galbraith, 1998, p. 90) Firms in the C sector produce standard machinery as well as consumption goods from existing machines and labor. The C sector does not operate in a market that is strictly competitive; rather, firms here enjoy a certain degree of monopoly power and are thus able to earn a significant profit. Monopoly power here derives from the ability of firms to develop a unique manufacturing capacity through the application and use of new machines. (Galbraith, 2001a, 37-38) Wages in the C sector are higher than in the S sector, because workers here have a somewhat specialized knowledge of the new machines used in production. This specialized knowledge allows them to earn—in Galbraith's words--a "scarcity premium," which comes in the form of higher wages. (Galbraith, 2001b, pp. 9-10)

The third sector is the *K sector*, K standing for knowledge, or capital goods. The K sector produces most of the new capital equipment used by the C sector. It also creates new consumer products and develops new means of production. The K sector is *highly* monopolistic as new capital goods typically reflect recent technological innovations, which make them truly unique. Moreover, if a new capital product can be successfully brought to the marketplace—which occurs when it is adopted by the C-sector—it has the potential to become the industry standard. Profits in the K-sector are thus very high, as they reflect a "winner-take-all proposition." (Galbraith, 2001b, pp. 10-11); (Galbraith 1998, pp. 90-91) Wages in the K-sector are also higher than in the C sector because the design and development of new capital goods typically require a high degree of specialization and knowledge on the part of the worker. Workers here are thus able to earn—to an even greater extent than in the C-sector—a "scarcity premium," in the form of very high wages. (Galbraith , 1998, 91-92)

In Galbraith (2001a) and (2001b), the author applies this taxonomy to explain *changes* in the inequality of wages over the *short-term course of the business cycle*. As he describes it, because the K sector produces capital products, it relies on strong investment demand, which typically occurs at the beginning of the business cycle. In the early stages of the business cycle, therefore, wages in the K sector are at their highest relative to both the C and S sectors. Inequality between the C and S sectors is also highest at the beginning of the business cycle because this is when consumption demand has dropped to its lowest point. When consumption demand falls, moreover, prices and wages in both the C and S sectors fall, but they do so at a *slower rate* in the C sector. This occurs because while the monopolistic C sector faces a downward sloping demand curve, the competitive S sector faces a perfectly elastic demand curve. (Galbraith, 2001a, pp. 10-11)

In the later stages of the business cycle, however, when investment demand falls and consumption demand grows, prices and wages in the K-sector fall relative to both the C and S sectors. At the same time, prices and wages rise in both the C and S sectors, though at a faster rate in the S sector for the reason cited above, and inequality between the C and S sectors falls. Inequality among all three sectors is, therefore, lowest during the later stages of the business cycle. Therefore, as was seen with the distribution of income between aggregate wages and aggregate profits, *changes* in the degree of overall inequality in the wage structure—at least in the short-term—are closely linked with macroeoconomic conditions; tending to rise when investment demand is strong and consumption demand weak, and decreasing when the reverse is true. Simply stated, inequality is anti-cyclical: falling during periods of strong economic growth or expansion, and rising during recessions and periods of weak growth. (Galbraith, 2001b, pp. 9-10).

In Galbraith's view, this theory is in fact a good description of a country on the downward-sloping portion of Kuznets' inverted 'U' curve—described earlier in the chapter—where growing national income over time leads to decreasing inequality.[20] While therefore embracing the original theory of the Kuznets curve, Galbraith also updates it to reflect the more recent changes in industrial structure that have occurred in

[20] It should be noted that Kuznets (1955) was explicit in that he was describing changes in the "secular" distribution of income, or changes that were long-term in nature and occurred independently of the business cycle; while Galbraith (2001) appears to equate the short-term and long-term, arguing that the key process at work was economic growth.

the most advanced industrial economies since the time of Kuznets. What Galbraith suggests, in fact, is the existence of an *augmented Kuznets curve*, which starts with the inverted U, where inequality first rises and then falls, but which then *turns up again for a few countries at the highest income levels*. A graphical illustration is presented in Figure 6. Income inequality begins to grow again in a few of the most advanced industrial economies—such as the US, UK, and Japan—because these countries have large K-sectors. These countries have large K-sectors, moreover, because they provide advanced capital goods not only to their domestic markets, but to much of the rest of the world. (Conceicao & Galbraith, 2001a, p. 157)

In later work—Galbraith (2012)—the author would be more explicit about the short-term versus long-term dynamics of changes in earnings inequality. Here, Galbraith would note—as Kuznets had originally suggested—that industrial structure, and its change over time, are what determine the level of earnings inequality, and its "secular" or long-term change over time. In the short-term, moreover, what changes is the *degree* of inequality among the industrial sectors: rising during expansions, and falling during recessions. In Galbraith (2012), the author would also add a new sector to his original taxonomy—the high-wage financial services sector—which represents another high-wage sector that (like the K-sector) has contributed to the growth of earnings inequality in advanced countries like the U.S. Galbraith also mentions the decline of manufacturing (C-sector) and the growth of low-wage services (S-sector) as being important elements in the changing industrial structure of the U.S. and the growth of earnings inequality.

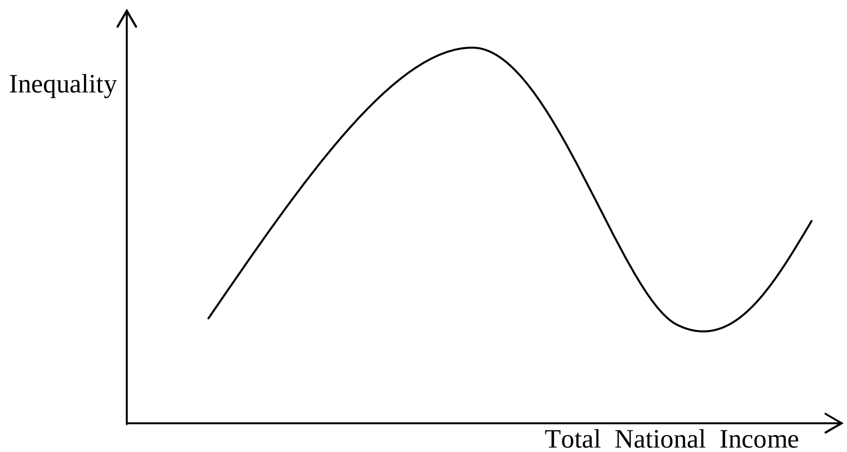

Figure 6: Augmented Kuznets Curve

Conclusion

Having reviewed the theoretical and empirical literature on income and earnings inequality, it is clear that it spans a wide-range of ideas as well as empirical methods. To a large degree, the diversity in the theoretical literature simply reflects the fact that there are a number of distinct—and often conflicting—schools of economic theory in the field of economics. Each school, moreover, comes with its own set of assumptions as well as implications for public policy. The choice of which theory to adopt as a model and to test with empirical research, therefore, may simply depend on the theoretical orientation of the researcher. There are, however, some more general criteria that might be considered when making the choice of a theoretical model. Some of these criteria and the justification for the theoretical model to be adopted here are discussed in the following chapter.

CHAPTER 3: THEORETICAL MODEL, HYPOTHESES, AND RESEARCH QUESTIONS

Introduction

This chapter begins with a critique of the prevailing theory of earnings inequality—namely the neoclassical labor market thesis. This is followed by a discussion of, and justification for, an alternative theory which is to be used as the basis for the theoretical model to be explored here. Next, an initial description is provided of the empirical research to be conducted in the study, and the two key hypotheses to be explored and tested with this research. The first hypothesis is descriptive, and relates to the rate of growth of earnings inequality in metro areas in the U.S. over the 1990 to 2004 period, as well as to how this growth has varied across metros. The second hypothesis is based on a specific theoretical model which seeks to explain the causes of the growth of earnings inequality in metro areas. The theoretical model is fully described below.

Neoclassical versus Post-Keynesian Theory

Currently, the most influential theory of earnings inequality is the neoclassical dual labor market thesis, which argues that the growth of earnings inequality in the U.S. over recent decades is primarily a result of changes in the supply and demand for skilled versus unskilled labor. The most important change in the market for skill, moreover, as been an increase in the demand for skilled labor due to skill-biased technological change (SBTC).

The SBTC explanation for earnings inequality is not without it critics, however. Two examples are Card and DiNardo (2002) and Lemieux (2008). In Card and DiNardo (2002), the authors argue that the SBTC thesis is undermined by the lack of correlation in timing between the increase in the use of technology in the workplace in the U.S. and the growth of earnings inequality. For example, a large proportion of the growth of earnings inequality in the 1980s had already occurred by 1984, which is the year the IBM-AT was first introduced. (774)

In Lemieux (2008), the author notes that one of the weaknesses of the SBTC thesis is that it cannot account for the fact that earnings inequality did not grow in other advanced industrial countries in the 1980s as it did in the U.S. (p. 23) In Lemieux's view, the reason for this difference between the U.S. and other advanced countries has to do with differences in wage setting institutions, such as minimum wage laws. An additional weakness of the SBTC thesis noted by Lemieux relates to the fact that it has been found empirically that the growth of earnings inequality in the U.S. has been concentrated at top of the earnings distribution. This flies in the face of the SBTC thesis, one of the general conclusions for which is that inequality has grown throughout the earnings distribution in the U.S., and not just at the top. (p. 25)

In addition to these and other assessments of the prevailing neoclassical theory of earnings inequality, probably the most well-developed and sustained critique has been provided by Galbraith (1998) and (2012), and (Conceicao & Galbraith, 2001a).

Galbraith questions the validity of the SBTC thesis on a number of grounds, including the problem of timing—as in Card and DiNardo (2002)—as well as the lack of correlation between the assumed growth of technology in the 1980s and empirical measures of productivity growth. In addition to these issues, however, Galbraith also discusses what might be viewed as a more fundamental weakness of the theory, which is that it relies on concepts and ideas that are over-broad and ill-defined, making them problematic analytically. Their lack of clear definition also makes them hard to measure or prove empirically. For example, there is no standard method for measuring technology or its rate of change over time; nor is there a standard for measuring 'skill bias.' In Galbraith's words:

> …we have no direct way to know whether it was technological change or some other factor that drove up the relative pay of more educated workers after 1980. The degree of "skill bias," like the rate of technological change itself, is an inference rather than an observation. (Galbraith, 1998, p. 27)

The over-reliance on inference versus empirical proof in the development and defense of a theory might indeed be taken as a sign of its weakness. It is interesting to note, moreover, that both the earlier ability and human capital theories similarly tried to apply broad, complex, and ill-defined concepts—such as ability and level of education—to explain income inequality. This too necessitated the use of inference. In the case of ability theory, for example, the original inference was made that the distribution of income was simply determined by the distribution of ability. Moreover, because ability was normally distributed, then income must be as well. It was only after the empirical work of Pareto, moreover, that this original inference had to be re-examined.

There is, in fact, a compelling alternative to the dual labor market thesis, the basic elements of which can be found in the earlier-discussed works of Kuznets (1955), the de-industrialists such as Bluestone and Harrison (1982), and Galbraith (1998); (2001a); (2001b); (2012). Each of these authors essentially starts with the same premise that the level of earnings inequality in an economy, and its change over time, is largely determined by its industrial structure, and its change over time. There are some differences among these authors, which generally come down to three things: their taxonomy of industrial structure; which industries they think are the most important in driving changes in the level of earnings inequality; and their theoretical explanation for how and why certain industries contribute to changes in earnings inequality.

To reiterate, in Kuznets (1955), the author had originally described a two-sector economy: agriculture and industrial manufacturing. During the early stages of industrialization—when a nation's manufacturing sector is still small—earnings inequality grows over time. Once the process of industrialization had deepened and matured—and the manufacturing sector had grown to a significant size—earnings inequality would change direction and begin to fall.

Subsequently, in the 1980s, the de-industrialists—such as Bluestone and Harrison (1982)—would similarly identify the manufacturing sector as an important source of middle-income jobs in the American economy, citing its decline as the primary reason earnings inequality had begun to grow in the U.S. The de-industrialists would drop Kuznet's agricultural sector, however, replacing it with the new high-technology and growing retail trade and services sectors. While apparently less important than the decline of manufacturing, the emergence and growth of these two sectors had also contributed to the growth of earnings inequality. This was because earnings in the high-technology sector were well above average, while earnings in the retail trade and services sectors were well below.

Finally, Galbraith (1998); (2001a); (2001b); and (2012) would make more explicit a three-sector economy: the S-Sector (services); the C-Sector (consumption goods); and the K-sector (knowledge or capital goods). While Galbraith's taxonomy was similar to the de-industrialists, he did not stress the importance of the decline of the manufacturing sector—which generally corresponds to his C-sector—as being the major cause of growing earnings inequality in the U.S. Instead, it was the growth of the high-technology sector—corresponding generally to Galbraith's K-sector—that was the major reason for the growth in earnings inequality. The other important difference between Galbraith's work and that of the industrialists was that he provided a clear and coherent explanation for why average earnings varied across the three sectors. Earnings were lowest in the S-sector both because firms operated under competitive market conditions where profit margins are low, and workers in any case have very little leverage over their earnings. Earnings are higher in the C-sector because firms here operate with a degree of monopoly power—which translates into a higher level of profit—and workers are in a position to bargain for a share of these profits due to their scarcity premium. Earnings are highest in the K-sector, as firms here operate in a market that is highly monopolistic and thus enjoy monopoly profits. These high profits are shared with their staff in the form of high earnings, as workers have very specialized skills, making them key to the firm.

The chief appeal of the work of Kuznets, the de-industrialists, and Galbraith—particularly in contrast to the SBTC thesis—is that they rely on an economic phenomenon that is clearly defined and measureable—industrial structure—and which is therefore much easier to analyze and prove empirically. They also return the focus in explanations of earnings inequality to macroeconomic forces, forces that have been ignored in much of the literature on inequality since the 1980s. Moreover, it is the work of Galbraith in particular that provides the clearest and most up-to-date framework for interpreting and analyzing changes in earnings inequality in metro areas in the U.S. It is, therefore, Galbraith's theory—with some adjustments—that will provide the basic framework for the theoretical model to be used in this study. This model is fully described below.

First Hypothesis

This dissertation presents annual measures of earnings inequality within metropolitan areas in the United States for the years 1990 to 2004. These annual measures are calculated for each year for 255 metropolitan areas, and are comparable across time and between metros. Based on these results, it will be possible to test the **first hypothesis**, which is that: while earnings inequality grew significantly at the national level in the U.S. from 1990 to 2004, this growth was more significant as it occurred within a relatively small number of specific metropolitan areas. That is to say, the growth of earnings inequality in the U.S. generally over this period was spatially concentrated within certain metropolitan regions. Some of the broad research questions which naturally follow from this hypothesis include: 1. What proportion of the total population of metropolitan areas have experienced strong growth in earnings inequality over the 1990 to 2004 period? 2. In which metropolitan regions has the level and growth of earnings inequality been most significant? 3. For the high-inequality regions, how does the level and growth of earnings inequality generally compare to the level and growth at the national level?

Second Hypothesis

In addition to answering these straightforward empirical questions, a specific theoretical model regarding the causes of high levels and growing earnings inequality is tested. As discussed at the beginning of this chapter, the basis for the theoretical model to be tested here is supplied by the work of Kuznets (1955), the de-industrialists such as Bluestone and Harrison (1982), and Galbraith (1998); (2001); (2012). The proposed model begins with the general hypothesis that earnings inequality is a function of industrial structure. Galbraith's theory of earnings inequality—based on the K-C-S taxonomy of industrial structure—is then used as the model to explain how and why particular industries contribute to the growth of earnings inequality. The key sector of interest here, moreover, is the K-sector, which, in Galbraith's view, has been central to the growth of earnings inequality in the U.S. One significant change is made to Galbraith's taxonomy, however, which is the **addition of an F-sector, where F stands for financial services.** The financial services industry is added to Galbraith's taxonomy based on the proposition that firms here—in a way very similar to the K-sector—operate with a high degree of monopoly power, translating into monopoly profits. The monopoly power here is derived in part from the tremendous economies of scale that exist in the provision of financial services. One person or one firm can just as easily manage a portfolio of $100 million as they can $1 billion. This means that a relatively small number of firms can manage a large proportion of the total demand that exists for financial services at a given point in time. Moreover, workers in the F-sector receive a portion of these monopoly profits in the form of high wages and bonuses because they are responsible for establishing and maintaining relationships with clients/investors as well as other market participants. Frequent staff turnover, therefore, could result in a significant loss of profit for the firm.

In addition, this research uses Galbraith's taxonomy—with the addition of the F-sector—to interpret earnings inequality in metropolitan economies that are on the upward-sloping, high-income segment of the augmented Kuznets curve, where economic growth over time leads to growing income inequality. Applying this theoretical model as an explanation for rising earnings inequality in metros in the U.S. can be expressed by a **second hypothesis**, which is that: those metropolitan regions which experienced high levels and a significant growth of earnings inequality over the 1990 to 2004 period had industrial structures significantly weighted toward the high-wage information technology and/or financial services sectors. Moreover, it was the large size and rapid growth of these sectors which was largely responsible for the level and growth of earnings inequality in those metropolitan regions. Some of the research questions which follow from this hypothesis include: 1. How do the industrial structures of high-inequality regions compare with those of low-inequality regions? 2. Do high-inequality regions specialize in the information technology and/or financial services sectors whereas the low-inequality regions do not? 3. For the high-inequality regions, have the information technology and/or financial services sectors played an important role in the overall level and growth of earnings inequality?

In addition to focusing on the specific role of the financial services and information technology industries in the growth of earnings inequality in metropolitan areas, the more general hypothesis regarding the relationship between industrial structure and earnings inequality is also examined. There may in fact be additional industrial sectors--either in addition to or instead of the financial services and information technology industries--that have contributed significantly to the growth of earnings inequality in metropolitan areas. It will be important to take note of these and analyze how they relate to our theoretical model and the broader literature. A complete list of these additional industrial sectors will be provided in Chapter 4.

Finally, in order to provide a more rigorous test of the hypothesized relationship between the financial services and information technology industries and earnings inequality, it will be necessary to control for other possible explanatory variables. As has been discussed, the most influential theory of earnings inequality is the dual labor market thesis, which posits that individual earnings vary chiefly by the level of "skill." One measure of skill, moreover, is educational attainment. It will be useful, therefore, to control for the level of educational attainment in the model. In addition, while not as common in the literature, the potential influence of racial bias on earnings inequality is also of interest to many observers. For this reason, the influence of specific racial groups on earnings inequality will also be controlled for in the model. Finally, as noted in the literature review, the research on income inequality at the metro or city level has traditionally focused on population size, density, and growth rates as the key determinants of income inequality. For this reason, population growth will also be controlled for in the model. The list of specific variables to be used to represent the level of educational attainment, the size of specific racial groups, and the extent of population growth will be provided in Chapter 4.

CHAPTER 4: DATA AND METHODOLOGY

Introduction

This chapter describes the data and methodology used to measure earnings inequality in metropolitan regions—and at the national level—in the U.S. for the period 1990 to 2004. Also included is a description of the data and methodology used to measure industrial structure in metro regions. This is followed by a review of the statistical methods used—namely bivariate correlation and OLS regression—to measure the association between the measures of earnings inequality and industrial structure. Finally, the many potential issues involved with the proposed methodologies are reviewed.

Measuring Earnings Inequality in Metropolitan Areas using the Theil Statistic

This research applies a summary measure of inequality, Theil's *T* statistic, to metropolitan-level[21] annual employment and earnings data for the years 1990 to 2004. These data are available from the U.S. Bureau of Labor Statistic's (BLS) Covered Employment and Wages Program (CEW). The employment and earnings data from the CEW are grouped by industrial category, represented by the North American Industrial Classification System (NAICS).[22] The 6-digit level NAICS is used, which in the largest

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[21] The metropolitan area definitions utilized here are those defined by the Office of Management and Budget for 6/30/1999. The 6/30/1999 definitions include Metropolitan Statistical Areas (MSAs), Consolidated Metropolitan Statistical Areas (CMSAs), and Primary Metropolitan Statistical Areas (PMSAs). All data utilized here are for MSAs or PMSAs only; data for CMSAs were not used.

[22] The 2002 NAICS coding system was used.

metros can represent over 1,000 industrial categories, and in the smallest metros, close to 400 categories. Due to the fact that the data are grouped, the *between-group component* of the Theil statistic is used, which can be written as:

$$[1] \quad T' = \sum_{i=1}^{n} \left(\frac{p_i}{P} \right) \left(\frac{Y_i}{Y} \right) \log \left(\frac{Y_i}{Y} \right)$$

where *pi* is total employment in industrial group *i*, *P* is total employment for all industrial groups combined, *Yi* is average earnings for industrial group *i*, and Y is average earnings for all industrial groups combined.

It should be noted that the within-group component of the Theil statistic is omitted, and so the measurement is a lower-bound estimate of inequality. Theoretically, *T'* can range in value from zero, representing perfect equality—where every industrial group in a metro has the same average income—to log(P/pi(min)), or the natural logarithm of total employment for all groups combined divided by the total employment of the smallest group. The maximum occurs when the smallest group receives all earnings. (Hale, 2004, pp. 11-12); (Galbraith and Hale, 2004, pp. 3-4) In other words, *T'* has no absolute upper bound, but instead, its limit depends on the size of the population being studied. (Conceicao and Galbraith, 2001b). The larger the population being studied, moreover, the higher the upper limit of the Theil measure. The Theil measures are comparable across metros and time as long as the same industrial grouping structure—represented by the 6 digit NAICS—is consistently utilized.

The earnings and employment data from the BLS' CEW program used to calculate the Theil measures were aggregated at the county level so that consistent metro definitions could be constructed for every year of the period 1990 to 2004. It should be noted, however, that due to the confidentiality issues associated with the publicly-available CEW data at smaller geographic levels, it was necessary to obtain access to the confidential data files for the CEW program. Moreover, due to the fact that the CEW data are collected by the States themselves, permission was required from each State individually to obtain access to their data. There were, in fact, seven States that denied permission to access and use their data for this study, including: Pennsylvania, New York, Michigan, Massachusetts, New Hampshire, Florida, and Wyoming. These seven states account for 82 metro areas—out of a total of 337 in the nation overall—leaving a total of 255 metro areas that are included in this study.

In addition, one of the research questions posed in the previous chapter was concerned with how the level and growth of inequality at the metro level in the U.S. over the 1990 to 2004 period compared to the level and growth of inequality at the *national* level. The metro-level inequality measures just discussed can be compared to national-level inequality measures as long as the same method for measuring inequality at the metropolitan level is used to measure it at the national level. To calculate the national measures, therefore, we again apply the between-group component of the Theil statistic to employment and earnings data organized by industrial category at the 6-digit NAICS level. The only difference is that the geography being analyzed is a nation, rather than a metropolitan area.

Finally, as fully explained in Conceicao and Ferreira (2000), the Theil statistic has a unique and interesting property in that it is 'deconstructible.' This means that the term within the summation sign in equation [1]—referred to by Galbraith and Hale (2007) as the "Theil element"—can be used as an indication of the distinct contribution of each industrial sector to the level of earnings inequality in a given metro in a given year. By observing how these contributions change over time, moreover, it is possible to observe the significance of each industry's contribution to the *growth* of earnings inequality over time. The deconstructed Theil index will thus be used as an initial assessment of the role of specific industrial sectors in the growth of earnings inequality in metros over the 1990 to 2004 period.

An example of a deconstructed Theil statistic for the Jersey City, NJ PMSA is presented in Table 1 on the next page. Here, the Theil elements for each industry in 1990 and 2004 are displayed, along with the final summary measure of inequality for each year, which is displayed as the sum of the Theil elements at the bottom of the table. A few things should be noted about the results in Table 1. First, while the summary Theil index itself is always positive, each industry's Theil element can be either positive or negative (in numerical terms). If an industry's average earnings level is greater than the average for all industries combined in the metro, then its element will be positive. If its average earnings level is below the average for all industries combined, then its element will be negative. It is important to understand, however, that a sector's Theil element grows in importance in real terms as it moves away from zero, in either a positive or negative direction. Thus sectors with large negative Theil contributions can be making important contributions inequality, just as sectors with large positive contributions.

Table 1: Theil Elements for Jersey City, NJ PMSA, 1990 and 2004

Industry Name	Theil Element 1990	Theil Element 2004
Finance and insurance	0.0273	0.2536
Management of companies and enterprises	-0.0001	0.0111
Information	0.0118	0.0149
Arts, entertainment, and recreation	-0.0009	0.0001
Mining, quarrying, and oil and gas	0.0000	0.0000
Utilities	0.0041	0.0032
Educational services	-0.0003	-0.0018
State	0.0002	-0.0018
Real estate and rental and leasing	0.0004	-0.0020
Professional and technical services	0.0300	0.0274
Unclassified	-0.0002	-0.0031
Accommodation and food services	-0.0137	-0.0168
Other services, except public administration	-0.0021	-0.0056
Retail trade	-0.0241	-0.0287
Local	0.0028	-0.0045
Construction	0.0101	0.0010
Administrative and waste services	-0.0087	-0.0190
Manufacturing	0.0073	-0.0041
Federal	0.0117	0.0003
Wholesale trade	0.0221	0.0085
Health care and social assistance	-0.0052	-0.0209
Transportation and warehousing	0.0026	-0.0189
Theil Index (Sum)	**0.0753**	**0.1930**

Source: BLS data analyzed by author

In the case of the Jersey City metro, the sector with the largest increase in its Theil element (in either a positive or negative direction) over the 1990 to 2004 period was—by a wide margin—Finance and insurance. This sector's Theil element increased from (0.0273) in 1990 to (0.2536) in 2004. Although the *precise* impact of the Finance and insurance industry on the growth of earnings inequality cannot be quantified based on its Theil elements, this result can be taken as a strong indication of its importance in more general or qualitative terms.

Measuring Industrial Structure in Metropolitan Areas

Next, measures of *industrial structure* are calculated for each metro area for the two years 1990 and 2004. (The intervening years are not included)[23]. While the focus here is specifically on the financial services and information technology industries, the measures of industrial structure cover the entire economy of each metro area. Including all economic sectors in the analysis allows us to observe not only whether the hypothesized relationship between the financial services and information technology industries and earnings inequality exists, but whether other economic sectors have a significant relationship with earnings inequality as well.

For the purposes here, industrial structure is simply defined as the type and size of industries that exist in a given metropolitan economy. The most commonly used method

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[23] This is mainly due to time and resource constraints. A full time-series analysis which covers the intervening years is certainly possible.

to measure industrial structure in a geographical area is to calculate the proportion of its total working population employed in each of its industries, and then use that data to calculate employment-based location quotients. (Krikelas, 1992, p. 20) An employment-based location quotient is a measure of the concentration or specialization of an industry in a given geographical area—such as a metro—within the context of a *larger* geographic area—such as a nation. The location quotient is defined as:

$$[2] \quad LQ_{i,G} = \left(\frac{E_{i,G}}{E_G}\right) \div \left(\frac{E_{i,N}}{E_N}\right)$$

where $E_{i,G}$ is employment in industry *i* within geography *G*; E_G is total employment in geogaphy *G*; $E_{i,N}$ is employment in industry *i* nationally; and E_N is total employment nationally. When the LQ for a given industry in a given geography is greater than one, this indicates that the geography specializes in the industry, within the context of some larger geographical area—again, typically a nation. Where the LQ is less than one, this indicates that the geography does not specialize in that industry within a larger geographical context.

The interest here, however, is not in whether a metro area can be said to specialize in a given industry within the national context, but rather, simply the size of each industry relative to the sizes of the other industries in that metro. For our purposes, therefore, only the *numerator* of the employment-based Location Quotient presented in [2] is needed as a measure of industrial structure, as it represents the shares of employment accounted for by each industrial sector in a given metro.

In addition to employment-based Location Quotients, income or earnings-based Location Quotients are also sometimes used as measures of industrial structure. (Krikelas, 1992, p. 20) One example is Kozlowski (2006), who calculates earnings-based Location Quotients for different industries in metropolitan areas. (p. 4) There is an argument to be made that, as a measure of economic activity, earnings-based Location Quotients may in fact be preferable to employment-based measures, as earnings tend to reflect the economic value (or price) of the good or service being produced. An earnings-based location quotient is defined as:

$$[3] \quad LQ_{i,G} = \left(\frac{R_{i,G}}{R_G}\right) \div \left(\frac{R_{i,N}}{R_N}\right)$$

where $R_{i,G}$ is total earnings in industry *i* within geography *G*; R_G is total earnings in geography *G*; $R_{i,N}$ is total earnings in industry *i* for the nation; and R_N is total earnings for the nation. Again, as mentioned above, only the numerator of the earnings-based Location Quotient in [3] is needed to measure industrial structure. The numerator gives us the share of total earnings accounted for by each industry in each metro.

There are, therefore, two measures of industrial structure used in this study; the first will be referred to as the Employment Share (ES), which is defined as:

$$[4] \quad ES_{i,M} = \left(\frac{E_{i,M}}{E_M} \right)$$

where $E_{i,M}$ is employment in industry *i* within metro *M*; and E_M is total employment in metro *M*. The second measure is the Earnings Share (RS), which is defined as:

$$[5] \quad RS_{i,M} = \left(\frac{R_{i,M}}{R_M} \right)$$

where $R_{i,M}$ is total earnings in industry *i* within metro *M;* and R_M is total earnings in metro *M*. The usefulness of each measure will generally be assessed in terms of the strength of its statistical relationship with the Theil. Based on this standard, moreover, it might be found that one measure is preferable to the other as a measure of industrial structure.

The source of the data used to create the share measures for each metro are in fact the same as that used to calculate the Theil statistic: the BLS' Covered Employment and Wages Program. The difference here is that instead of being grouped at the 6-digit NAICS level, the data are grouped at the Supersector level, which includes just 13 industrial sectors. Presented in Table 2 is a list of these 13 sectors, along with an example of the Employment and Earnings Shares calculated for the Stamford-Norwalk, CT PMSA in 1990. These are the share measures which are calculated for each industry in each metro for both 1990 and 2004. Again, the intervening years are not included.

Table 2: Supersectors, Employment and Earnings Shares, Stamford-Norwalk PMSA, 1990

Sector	Employment Share	Earnings Share
Financial Activities	0.0816	0.1164
Information	0.0304	0.0343
Manufacturing	0.1952	0.2287
Professional and Business Services	0.1466	0.1787
Construction	0.0341	0.0346
Education and Health Services	0.1034	0.0872
Federal Government	0.0125	0.0117
State Government	0.0162	0.0136
Local Government	0.0721	0.0652
Natural Resources and Mining	0.0009	0.0009
Leisure and Hospitality	0.0651	0.0274
Other Services	0.0365	0.0207
Trade, Transportation, and Utilities	0.2050	0.1801
	1.0000	1.0000

It should also be noted that the *publicly-available* earnings and employment data from the CEW were used to calculate the share measures.[24] Moreover, even at the high level of aggregation that exists at the Supersector level, there was some data suppression due to confidentiality rules. In the context of the size of the dataset, however, the degree of data suppression was low. For the 1990 data, for example, 4.6 percent of the observations in

[24] As opposed to the confidential data files that were used to calculate the Theil measures; it should also be noted that the Supersector-level data were collected at the county level, so that consistent metro definitions could be used for 1990 and 2004.

the CEW dataset were missing. In 2004, this rate dropped to 2.4 percent. The missing data items for each year had to be imputed.[25]

Assessing the Influence of Industrial Structure on Earnings Inequality in Metropolitan Areas

In order to measure, then, the influence of industrial structure generally—and the financial services and information technology industries in particular—on earnings inequality in metropolitan areas, the statistical relationship between the Theil measures and the (ES) and (RS) measures are examined. This relationship is examined on a cross-sectional basis for both 1990 and 2004 using simple bivariate correlations.   This is followed by a fuller and more rigorous test of the statistical relationship between the *change* in earnings inequality over the period 1990 to 2004—as represented by the percent change in the Theil statistic—and the *change* in industrial structure over that time—as represented by the point change in the (ES) and (RS) measures. Simple bivariate correlation analysis is again utilized, but is then followed by the application of OLS regression analysis.

The OLS regression model will take the following mathematical form:

$$[6] \qquad \boldsymbol{Y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n + \mu,}$$

[25] A full explanation of the ad hoc imputation method is provided in the appendix.

where the dependent variable Y represents the percent change in the Theil statistic (1990 to 2004); the $x_1 \ldots x_n$ represent the explanatory and control variables; and the μ represents the random variable. The explanatory variables are listed in Table 3.

Table 3: Explanatory Variables

Change Earnings Share Finance
Change Earnings Share Information
Change Earnings Share Manufacturing
Change Earnings Share Professional & Business Services
Change Earnings Share Construction
Change Earnings Share Education & Health Services
Change Earnings Share Federal Government
Change Earnings Share State Government
Change Earnings Share Local Government
Change Earnings Share Natural Resources & Mining
Change Earnings Share Leisure & Hospitality
Change Earnings Share Other Services
Change Earnings Share Trade, Transportation, & Utilities

In addition, it is important in the regression model to control for other variables that might have an impact on the growth of earnings inequality. The list of control variables to be included in the regression model appears in Table 4. As previously discussed, skill, racial composition, and population size have all been discussed in the literature as possible factors affecting earnings inequality. It will be important, therefore, to attempt to control for these factors. As an indicator of skill, the proportion of the population with a bachelor's, master's, or a doctoral degree is used. Moreover, the interest here is in controlling for the influence of both the *level of skill* and *changes in the level of skill* on the growth of earnings inequality over the 1990 to 2004 period. For this reason, both the level proportion—calculated as an average of the proportions in 1990 and 2004—and the change in the proportions from 1990 to 2004 is used. In term of racial composition, the proportion of the population that is Black and the proportion that is Hispanic are used as control variables. As was the case with skill, the interest here is in controlling for both the level proportions as well as the change in the proportions on the growth of earnings inequality. For this reason, both the level proportions—calculated as an average of the proportions in 1990 and 2004—and the change in the proportions from 1990 to 2004 are used. Finally, the impact of population growth on the growth of earnings inequality will be controlled for by adding the percent change in population from 1990 to 2004 to the model.

Table 4: Control Variables

Percent Change Population (1990 to 2004)
Average Proportion Black (1990 and 2004)
Average Proportion Hispanic (1990 and 2004)
Change Proportion Black (1990 to 2004)
Change Proportion Hispanic (1990 to 2004)
Average Proportion Bachelors (1990 and 2004)
Average Proportion Masters (1990 and 2004)
Average Proportion Doctorate (1990 and 2004)
Change Proportion Bachelors (1990 to 2004)
Change Proportion Masters or Professional (1990 to 2004)
Change Proportion Doctorate (1990 to 2004)

Methodological Issues

Data on Earnings

There are indeed a number of issues involved in the proposed methodology which need to be addressed. The first involves the earnings data itself. The earnings data from the BLS include all salary and earnings income by industry and geographic area for workers covered by State Unemployment Insurance laws. One limitation of this data, therefore, is that it excludes members of the armed forces, the self-employed, proprietors, domestic workers, unpaid family workers, and railroad workers covered by the railroad unemployment insurance system. BLS estimates, however, that the data cover 98 percent of all U.S. jobs; though the extent of coverage will likely vary by metropolitan area.

There are also a number of limitations involved in measuring the inequality of earnings, versus total income. In addition to earnings, total cash income includes returns on investments—such as interest, dividends, rents, and capital gains—as well as government transfers, and private retirement income. Moreover, providing a truly complete picture of *economic inequality* would require including in-kind benefits—such as health insurance, food stamps, housing assistance, and welfare benefits—as well as total asset wealth. However, it is also true that earnings continue to represent the largest component of income in the U.S.[26] (US Census, 2007, p. 9); (Galbraith, 1998, p. 83); (US CBO, 2001, appendix C) It is likely for this reason, moreover, that a number of observers have found that the single most important factor in the growth of household income inequality in the U.S. has been the growth of individual earnings inequality. (Gottschalk and Smeeding, 1997, p. 636); (US Census, 2000, p. 2)

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[26] According to the CBO, earnings account for over 70 percent of total income.

There is also the important methodological issue of measuring inequality across industrial categories, instead of across individuals, families, or households. Added to this is the fact that because just the between-group component of the Theil statistic is used, the inequality within each industrial category is not captured. However, as already noted, data on employment and earnings broken out at the 6-digit NAICS level represent anywhere between 400 and 1,000 industrial categories for a given metro. This large number of industrial groups allows the Theil statistic to capture more of the earnings inequality in a given metro than if, for example, the 5 or 4-digit NAICS level were used. In addition, Conceicao and Galbraith (2001b) and Conceicao, Galbraith, and Bradford (2001) have argued that there is a theoretical justification—based on some general assumptions—for using the between-group component of the Theil statistic to track the larger movement of inequality among households. Some empirical evidence supporting this conclusion, furthermore, is provided in Galbraith and Hale (2004).

Another issue—mentioned earlier—is that there are 82 metro areas not included in this research. These 82 metros, moreover, include some vey important ones in terms of size generally and perhaps more importantly, the size of their financial services and information technology industries. Two prime example are the New York, NY PMSA and the Boston, MA-NH PMSA. However, it is clear that not all of the financial services and information technology industries in the U.S. exist solely in New York and Boston—or any of the other 82 metros that are missing. Moreover, a large enough segment of these industries is accounted for by the 255 metros to allow for a test of the hypotheses proposed in this study.

Another issue involved in using the CEW earnings data from the BLS is that it represents pre-tax income. It is true, moreover, that the overall progressivity of the federal tax system in the U.S. means that the distribution of after-tax earnings will be more equal than the distribution of pre-tax earnings. In addition, there has been a decline in effective tax rates for low-income households since 1979. However, as shown in the CBO's after-tax income data, the increasingly unequal distribution of incomes overall in the U.S. have apparently overwhelmed the effects of any changes in tax laws. (US CBO, 2001, p. 15), (US Census, 2000, p. 9)

It should also be noted that the CEW data include part-time workers in addition to full-time workers. The earnings distribution for full-time workers only, moreover, is likely to be more equal than that for all workers, as part-time workers are going to earn less in a year. The importance or relevance of this issue, however, to some extent depends on the researcher's point of view. For some observers, including part-time workers is desirable because it reflects the reality of under-employment in the workforce. The fact that there are some people who want to work full-time but can only find part-time work represents the state of the labor market and therefore, a very important economic reality.

While there are some limitations to using the CEW data, it offers some key advantages vis a vis other methods. One important advantage is that the CEW data are consistently available on a quarterly or annual basis, which allows for the construction of dense and relatively long time series measures of inequality. Household income data, by contrast, are less available on such a consistent basis over time; and this is particularly true at the metro or county level in the U.S. For example, the recent U.S. Census report: "Household Income Inequality Within U.S. Counties: 2006-2010," relies on pooled household income data over a five year period to calculate inequality measures for just one point in time.

Another advantage of the CEW data are their accuracy and reliability. CEW data are not self-reported, as is the household income data from the U.S. Census Bureau's Current Population Survey. Instead, total payroll and employment data from the CEW are reported by each individual establishment to its respective state agency. Self-reported income data moreover, are prone to systematic measurement error as respondents to a survey perceive income-related questions as being personal and invasive. This is particularly true, moreover, for high-income people.

Statistical Measures of Inequality

Another methodological issue has to do with the inequality measure itself, i.e., the Theil statistic, and whether it is a reasonable measure of earnings inequality. The most common method to measure income or earnings inequality among individuals does not involve applying a summary measure of inequality, but rather, simply divides individuals into quintiles ranked by total income.[27] One can then measure the proportion of total income going to each quintile of the distribution, and observe how this varies over time. If we observe, as was the case with the CBO data, that the proportion of total income going to the top quintile has grown over time—while the proportions going to the other quintiles have changed only slightly—then we might conclude that income inequality has been rising. Different percentiles, such as deciles, may also be used, depending on the needs or interests of the researcher. (US Census, 2000, p. 4)

In addition to examining changes in percentiles, many researchers have used summary measures of inequality, like the Theil statistic, which provide a single statistic describing the degree of inequality in an income or earnings distribution overall. In choosing an inequality measure, there are a number of things to consider, including the type of income or earnings data that are available, and the particular properties of each measure which may or may not lend themselves to the specific research being conducted.

One common criterion for an inequality measure is that it be scale invariant, or mean independent. This means that the measure is not affected by changes in the mean income of the population or its size if the relative distribution within the population remains the same. (Sen, 1997, p. 139) Among other things, this means that if each individual's total

[27] Quintiles, or fifths, of the income distribution contain equal numbers of people.

income in a population is multiplied by some constant, i.e. each income changes at the same rate, the measure will not change. (Coulter, 1989, p. 18); (Allison, 1978, p. 866) Scale invariance also means that it is unnecessary, in the case of income data, to adjust for inflation. Applying the scale invariance standard allows us to rule out some of the most well-known measures of dispersion, including the *range*, the *standard deviation*, and the *variance*. (Allison, 1978, pp. 866-867)

Another important criterion for an inequality measure, first suggested by Dalton (1920), concerns the principle of transfers. This principle argues that whenever income is transferred from a rich to a poor person in a population, an inequality measure should decrease. Conversely, whenever income is transferred from a poor person to a rich person, an inequality measure should increase. (Dalton, 1920, p. 351) Applying the transfer principle allows us to rule out the *relative mean deviation* and *the standard deviation (or variance) of the logarithms* as desirable measures of inequality. In the case of the relative mean deviation, this measure is unaffected by income transfers that occur between individuals that are on the same side of the mean. For the logarithmic measures, they actually decrease with a transfer from a poorer to a richer individual if this transfer occurs at a high level of income. (Atkinson, 1970, pp. 254, 256); (Sen 1997, pp. 28-29, 32); (Allison, 1978, p. 868)

Among the more commonly-used inequality measures that satisfy both the principle of scale invariance and transfers include: the *coefficient of variation*, the *Gini coefficient*, and the *Theil statistic*. One important difference among these three measures is that they respond differently to transfers at different points in the income distribution. The coefficient of variation, for example, is equally sensitive to transfers at all income levels. (Sen, 1997, pp. 27-28); (Atkinson, 1970, pp. 255-256) The Gini coefficient is most sensitive to transfers around the center of the distribution, and the Theil statistic, like the logarithmic measures, is most sensitive to transfers at lower levels of income. (Allison, 1978, pp. 868-869); (Atkinson, 1970, p. 256)

Another well-known measure is the *Atkinson Index,* which was developed with the aim of developing a measure of inequality that was directly based on a social welfare function. This index also satisfies the principles of scale invariance and transfers. The Atkinson index allows for the specification of a parameter (e) which sets the degree of inequality averseness in the measure. As (e) rises, the measure becomes more sensitive to transfers at the low end of the income distribution. Conversely, as (e) falls, the measure becomes more sensitive to transfers at the top of the income distribution. (Allison, 1978, pp. 873-874); (US Census 2000, p. 11) An important problem in using the Atkinson index is that by basing the measure on a social welfare function, it ceases to be a positive measure of inequality, and instead, becomes a normative measure of social welfare, a standard for which there is little agreement. (Allison, 1978, p. 878); (Sen, 1997, p. 38) For this reason, it is not an ideal measure to utilize.

In terms of choosing among the remaining three measures which satisfy the principles of scale invariance and transfers—namely, the Gini coefficient, the coefficient of variation, and the Theil statistic—there are a number of additional considerations. Allison (1978) has suggested that the choice among these three measures likely depends on the variable being examined. If the variable, like income, is assumed to have a diminishing marginal utility, then the Theil statistic, which decreases in sensitivity as income increases, would likely be preferable. If the utility of a variable does not change, however, then the coefficient of variation might be the best choice. (Allison, 1978, p. 869)

Another important consideration in choosing an inequality measure has to with the availability and format of the income or earnings data itself. Annual data on income or earnings among individuals--while commonly available at the national level in the U.S.--are much less commonly-available at the state, metropolitan, or county level, at least on a consistent and regular basis. Payroll and employment data organized or grouped by industrial category, on the other hand, are consistently available at the regional level. An inequality measure which is applicable to grouped data, therefore, could be applied to payroll and employment data organized by industrial category to construct long and dense time series measures of inequality for metropolitan regions in the U.S. Additionally, while the Gini coefficient and coefficient of variation are not readily applicable to grouped data, the Theil statistic was in fact developed expressly for this purpose. The Theil statistic is therefore an ideal index to use to measure the evolution of earnings inequality at the metropolitan level in the U.S. (Conceicao and Galbraith , 2001b, p. 263)

Measuring Industrial Structure

Finally, while the method used here for measuring industrial structure in each metro is straightforward and derivative of methods commonly-used in the regional development field, there are some limitations in using data at the Supersector level. The high level of aggregation of these data means we may be missing some important dynamics occurring within each industrial sector. It may not, for example, be that all types of financial services are associated with inequality, but rather more narrowly-defined and specific sectors within the broader industry. It can be argued, however, that there are substantial differences between these sectors—in terms of employment and earnings—which are likely sufficient to capture some of the variation in the levels and changes in earnings inequality.

CHAPTER 5: RESULTS AND FINDINGS

Introduction

To reiterate, this study seeks to test two specific hypotheses regarding earnings inequality in metropolitan areas in the US. The **first hypothesis** is that: *while earnings inequality grew significantly at the national level in the U.S. from 1990 to 2004, this growth was more significant as it occurred within a relatively small number of specific metropolitan regions. That is to say, the growth of earnings inequality in the U.S. generally over this period was spatially concentrated within certain metropolitan regions.* Moreover, the **second hypothesis** is that: *those metropolitan regions which experienced high levels and a significant growth of earnings inequality over the 1990 to 2004 period had industrial structures significantly weighted toward the high-wage information technology and/or financial services sectors. Moreover, it was the relatively large size and rapid growth of these sectors that was largely responsible for the level and growth of earnings inequality in those metropolitan regions.*

With this in mind, this chapter is divided into three sections. Section one provides a description of the levels of inequality—as measured by the Theil statistic—in metro areas for two years: 1990 and 2004. Examining the cross-sectional inequality measures for each year is done in part for descriptive purposes, but also allows for an initial test of the **first hypothesis** regarding changes in the levels and spatial dynamics of earnings inequality in metro areas over this period. Section one continues with a description of the measures of industrial structure—the Employment Shares (ES)s and Earnings Shares (RS)s—for metro areas in 1990 and 2004. Analyzing the cross-sectional industrial structure measures is done primarily for descriptive purposes. It will be useful to know, for example, what the measures say about the industrial structure of metros and how this has changed over time. In addition, it will be useful to know whether the two types of measures—(ES) versus (RS)—offer similar results in terms of their descriptions of the industrial structure of metros.

Section one finishes with a review of some measures of bivariate correlation between the Theil statistic and the (ES) and (RS) measures for each sector, with a focus on the financial services and information technology sectors. As before, this is done separately for 1990 and 2004. The correlation measures for the financial services and information technology sectors provide an initial test of the **second hypothesis** regarding the relationship between these two sectors and earnings inequality in metro regions. Also of interest here is how this relationship may have changed over time. The correlation measures for the other industrial sectors are also examined to observe whether they too have some relationship with earnings inequality, and whether this relationship may have changed over time.

Section two moves beyond the cross-sectional analysis, focusing solely on the *change* in earnings inequality in metro areas—as measured by the percent change in the Theil statistic—over the 1990 to 2004 period. Both the rate of growth of inequality in metros over this period, as well as its spatial distribution across metros, will be examined. Looking at the change measures directly—as opposed to comparing the cross-sectional measures as in section one—provides an additional and perhaps clearer test of the **first hypothesis** regarding the spatial concentration of the growth of earnings inequality in the US. Also included in Section two is a presentation of time-series plots of the annual inequality measures for metros over the 1990 to 2004 period. The time series plots will offer additional insights into *how* earnings inequality evolved over the 1990 to 2004 period. In addition, the time-series plots for metros will be compared to a plot of annual inequality measures for the U.S. as a whole. The interest here will be in whether—as also implied in the **first hypothesis**—earnings inequality grew at a faster rate in certain metro areas than it did at the national level. Finally, following the time-series analysis, Section two finishes with an exploration of the deconstructed Theil statistic for the top five metros with the highest rates of earnings inequality growth over the 1990 to 2004 period. The Theil deconstruction will provide an initial examination of the relationship between the financial services and information technology sectors—as well as the other sectors—and earnings inequality.

Section three concludes the chapter with an examination of the statistical relationship between the *change* in the (ES) and (RS) measures for financial services and information technology—along with the other industrial sectors—and the change in earnings inequality over the 1990 to 2004 period. This final part provides a more rigorous test of the **second hypothesis** regarding the specific role of the financial services and information technology industries in the growth of earnings inequality. The analysis here begins with a description of the measures of *change* in industrial structure—as measured by the change in the (ES)s and (RS)s—over the period 1990 to 2004. This is followed by the statistical analysis, which includes measures of bivariate correlation between the change in the (ES)s and (RS)s for finance and information technology—as well as the other economic sectors—and the percent change in the Theil statistic. The analysis also includes the presentation of a formal quantitative model based on OLS regression. The OLS regression model uses the percent change in the Theil as the dependent variable, and the measures of change in the (ES)s and (RS)s for each economic sector as the independent variables. Also included in the regression model are variables controlling for educational attainment, race, and population growth.

Section 1: Earnings Inequality and the Nature of Industrial Structure at the Metropolitan Level: 1990 and 2004

Measures of Earnings Inequality: 1990 & 2004

To begin, the level measures of earnings inequality in 1990 and 2004 are examined. The basic descriptive statistics for the Theil in 1990 and 2004 are displayed in Table 5. The highest Theil measure in 1990 is (0.1663)—the Richland-Kennewick-Pasco, WA MSA—and the lowest measure is (0.0586)—the Hickory-Morganton-Lenoir, NC MSA, for a range of (0.1077). The mean measure is (0.1119), the median is (0.1110), and the standard deviation is (0.0198). The basic descriptive statistics for Theil 2004 also appear in Table 5. The highest Theil measure in 2004 is (0.3749)—the Stamford-Norwalk PMSA—and the lowest measure is (0.0754)—the Elkhart-Goshen, IN MSA, for a range of (0.2995). The mean measure is (0.1284), the median is (0.1248), and the standard deviation is (0.0267).

In comparing the descriptive statistics for the Theil in 1990 and 2004, we observe that both the mean and median level of earnings inequality in metro areas did increase over this period, mirroring the growth of inequality at the national level. The mean grew from (0.1119) in 1990 to (0.1284) in 2004—an increase of 14.7 percent—and the median grew from (0.1110) in 1990 to (0.1248) in 2004—an increase of 12.4 percent. The higher rate of growth for the mean versus the median initially suggests that the Theil 2004 measures have more unusually high values than the Theil 1990 measures. The wider distribution of the Theil 2004 measures is also reflected in an increase in the standard deviation—which grew from (0.1980) in 1990 to (0.2607) in 2004—and an increase in the range—which grew from (0.1077) in 1990 to (0.2995) in 2004.

Table 5: Descriptive Statistics, Theil 1990 and 2004

	n	**Mean**	**Median**	**Std Dev**	**Min**	**Max**	**Range**
Theil 1990	255	0.1119	0.1110	0.0198	0.0586	0.1663	0.1077
Theil 2004	255	0.1284	0.1248	0.0267	0.0754	0.3749	0.2995

A visual representation of the Theil 1990 and Theil 2004 distributions is presented in Figure 7. In Figure 7a, we see the distribution for the Theil 1990 measures, and it is close to being normal, though with a slight positive skew. In figure 7b, we see the distribution for the Theil 2004 measures, which appears to be positively skewed with a right-side tail. Comparing the two histograms reveals a striking difference between the spatial distribution of inequality measures across metros in 1990 versus 2004. This difference reflects the fact that while inequality in 1990 was evenly distributed across metropolitan areas—where the level of inequality for most metros was close to the mean—by 2004, a small group of metros had emerged which had very high levels of inequality—again relative to the mean level for all metros in that year.

A further demonstration of the change in the spatial dynamics of the metro-level inequality phenomenon between 1990 and 2004 is reflected in the dramatic change in which specific metro areas had the highest levels of earnings inequality in each year. Presented in Table 6 is a list of the top 20 metros with the highest levels of inequality in 1990 and 2004. The difference between the two lists is substantial, as there are just 7 metros that appear in the top 20 for both years. It is interesting to note that many of the metros that are on the list in 1990 but not in 2004 are in the Midwest. Moreover, a number of the metros that do not appear on the list in 1990, but do appear in 2004, are in California and Texas.

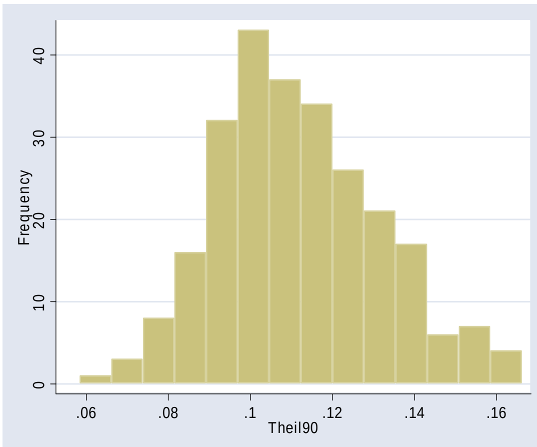

Figure 7a: Histogram, Theil 1990

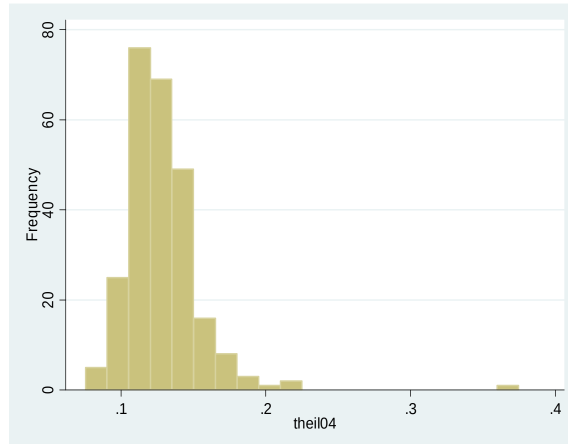

Figure 7b: Histogram, Theil 2004

Table 6: Top 20 Metro Areas with Highest Theil Measures, 1990 and 2004

Metro	Theil 1990	Metro	Theil 2004
*Richland-Kennewick.-Pasco, WA	0.1663	*Stamford-Norwalk, CT	0.3749
Waterloo-Cedar Falls, IA	0.1607	*Kokomo, IN	0.2213
Las Cruces, NM	0.1600	San Jose, CA	0.2155
Steubenville-Weirton, OH-WV	0.1599	San Francisco, CA	0.2029
*Kokomo, IN	0.1571	Ventura, CA	0.1943
*Stamford-Norwalk, CT	0.1553	Jersey City, NJ	0.1924
Janesville-Beloit, WI	0.1540	Brazoria, TX	0.1845
Provo-Orem, UT	0.1522	*Richland-Kennewick-Pasco, WA	0.1801
*Davenport-Moline-Rock Isl, IA-IL	0.1515	*Racine, WI	0.1797
*Peoria-Pekin, IL MSA	0.1513	Santa Cruz-Watsonville, CA	0.1773
*Beaumont-Port Arthur, TX	0.1511	Boulder-Longmont, CO	0.1740
*Racine, WI	0.1478	*Davenport-Moline-Rock Isl, IA-IL	0.1687
Gary, IN	0.1467	Galveston-Texas City, TX	0.1678
Cumberland, MD-WV	0.1457	*Beaumont-Port Arthur, TX	0.1670
Corpus Christi, TX	0.1447	San Angelo, TX	0.1664
Green Bay, WI	0.1446	*Peoria-Pekin, IL	0.1643
Dubuque, IA	0.1442	Houston, TX	0.1630
Mansfield, OH	0.1427	Memphis, TN-AR-MS	0.1627
Kankakee, IL	0.1423	Huntsville, AL	0.1605
Muncie, IN	0.1421	Duluth-Superior, MN-WI	0.1593

* metro appears on 1990 and 2004 lists.

Overall, the histograms, descriptive statistics, and the top 20 lists for the Theil measures in 1990 and 2004 clearly demonstrate that there was a marked change in both the level and spatial dynamics of earnings inequality in metro areas over the period. The level of earnings inequality clearly grew, as reflected in the increase of the mean and median measures—which grew by 14.7 percent and 12.4 percent respectively. The change in spatial dynamics came as high levels of earnings inequality in 2004 were concentrated in a relatively small number of metro areas, just as suggested in the **first hypothesis.**

Measures of Industrial Structure: 1990 & 2004

Now that the inequality measures for 1990 and 2004 have been examined, we move to review the measures of industrial structure for each year. Again, we are using two measures of industrial structure: the Employment Share (ES) for each industry in a metro, and the Earnings Share (RS) for each industry in a metro. Presented in Table 7 are the basic descriptive statistics for the (ES)s and the (RS)s for 1990 and 2004. Looking at the data for 1990, we observe that the (ES) measures for each industry are highly correlated with the (RS) for each sector. This is true both in terms of the value of the share measures themselves, as well as for how these measures rank the sectors in terms of relative size. For example, based on the (ES)s, the largest sector in 1990 was Trade, Transportation & Utilities, (mean (ES) = (0.207)), followed by Manufacturing, (mean (ES) = (0.165)). Based on the (RS)s for 1990, the same two sectors are still the largest, though Manufacturing is first (mean (RS) = (0.210)), followed by Trade,

Table 7: Descriptive Statistics, Employment and Earnings Shares, 1990 and 2004

Employment Shares 1990	**n**	**Mean**	**Median**	**Std Dev**	**Min**	**Max**	**Range**
ES Finance 1990	255	0.0525	0.0492	0.0197	0.0201	0.2072	0.1871
ES Information 1990	255	0.0221	0.0201	0.0092	0.0054	0.0689	0.0635
ES Manufacturing 1990	255	0.1650	0.1512	0.0825	0.0162	0.5199	0.5037
ES Prof & Bus Services 1990	255	0.0766	0.0678	0.0317	0.0279	0.2346	0.2067
ES Construction 1990	255	0.0482	0.0443	0.0160	0.0206	0.1563	0.1357
ES Educ & Health Servcs 1990	255	0.0988	0.0970	0.0301	0.0396	0.3165	0.2769
ES Federal Government 1990	255	0.0320	0.0220	0.0344	0.0034	0.3149	0.3115
ES State Government 1990	255	0.0487	0.0339	0.0502	0.0013	0.3776	0.3763
ES Local Government 1990	255	0.1025	0.0971	0.0302	0.0245	0.2473	0.2228
ES Nat Res & Mining 1990	255	0.0226	0.0071	0.0430	0.0007	0.2739	0.2732
ES Leisure & Hospitality 1990	255	0.0915	0.0860	0.0346	0.0417	0.3970	0.3553
ES Other Serivces 1990	255	0.0321	0.0316	0.0071	0.0169	0.0698	0.0529
ES Trade, Transp, & Util 1990	255	0.2071	0.2068	0.0337	0.1301	0.3730	0.2429
Earnings Shares 1990							
RS Finance 1990	255	0.0558	0.0504	0.0270	0.0194	0.3024	0.2830
RS Information 1990	255	0.0271	0.0241	0.0142	0.0059	0.1095	0.1036
RS Manufacturing 1990	255	0.2104	0.1946	0.1085	0.0131	0.6144	0.6013
RS Prof & Bus Services 1990	255	0.0787	0.0677	0.0434	0.0228	0.3672	0.3444
RS Construction 1990	255	0.0534	0.0505	0.0185	0.0217	0.1511	0.1294
RS Educ & Health Servcs 1990	255	0.1020	0.0971	0.0344	0.0344	0.3687	0.3343
RS Federal Government 1990	255	0.0445	0.0308	0.0477	0.0049	0.4485	0.4436
RS State Government 1990	255	0.0577	0.0409	0.0609	0.0012	0.4824	0.4812
RS Local Government 1990	255	0.1070	0.0988	0.0393	0.0294	0.3298	0.3004
RS Nat Res & Mining 1990	255	0.0211	0.0069	0.0362	0.0003	0.2317	0.2314
RS Leisure & Hospitality 1990	255	0.0376	0.0321	0.0284	0.0168	0.3467	0.3299
RS Other Serivces 1990	255	0.0210	0.0205	0.0058	0.0093	0.0554	0.0461
RS Trade, Transp, & Util 1990	255	0.1837	0.1823	0.0413	0.0898	0.3411	0.2513
Employment Shares 2004							
ES Finance 2004	255	0.0532	0.0490	0.0207	0.0207	0.1602	0.1395
ES Information 2004	255	0.0200	0.0179	0.0096	0.0057	0.0615	0.0558
ES Manufacturing 2004	255	0.1179	0.1058	0.0648	0.0124	0.5103	0.4979
ES Prof & Bus Services 2004	255	0.1024	0.0965	0.0339	0.0464	0.2232	0.1768
ES Construction 2004	255	0.0544	0.0527	0.0148	0.0240	0.1270	0.1030
ES Educ & Health Servcs 2004	255	0.1283	0.1229	0.0352	0.0598	0.3852	0.3254
ES Federal Government 2004	255	0.0227	0.0169	0.0214	0.0025	0.1844	0.1819
ES State Government 2004	255	0.0461	0.0329	0.0437	0.0027	0.3214	0.3187
ES Local Government 2004	255	0.1089	0.1042	0.0321	0.0270	0.2545	0.2275
ES Nat Res & Mining 2004	255	0.0179	0.0051	0.0373	0.0001	0.2491	0.2490
ES Leisure & Hospitality 2004	255	0.1009	0.0959	0.0316	0.0520	0.3575	0.3055
ES Other Serivces 2004	255	0.0317	0.0310	0.0070	0.0170	0.0639	0.0469
ES Trade, Transp, & Util 2004	255	0.1950	0.1941	0.0273	0.1133	0.3250	0.2117
Earnings Shares 2004							
RS Finance 2004	255	0.0677	0.0575	0.0378	0.0236	0.2952	0.2716
RS Information 2004	255	0.0261	0.0218	0.0167	0.0055	0.1054	0.0999
RS Manufacturing 2004	255	0.1585	0.1416	0.0914	0.0106	0.6125	0.6019
RS Prof & Bus Services 2004	255	0.1085	0.0941	0.0503	0.0375	0.3897	0.3522
RS Construction 2004	255	0.0579	0.0565	0.0174	0.0200	0.1282	0.1082
RS Educ & Health Servcs 2004	255	0.1330	0.1290	0.0435	0.0526	0.4593	0.4067
RS Federal Government 2004	255	0.0363	0.0268	0.0355	0.0034	0.3242	0.3208
RS State Government 2004	255	0.0536	0.0379	0.0549	0.0022	0.4275	0.4253
RS Local Government 2004	255	0.1106	0.1000	0.0414	0.0335	0.2831	0.2496
RS Nat Res & Mining 2004	255	0.0166	0.0048	0.0313	0.0001	0.2117	0.2116
RS Leisure & Hospitality 2004	255	0.0403	0.0356	0.0247	0.0178	0.2818	0.2640
RS Other Services 2004	255	0.0200	0.0198	0.0049	0.0106	0.0436	0.0330
RS Trade, Transp & Util 2004	255	0.1699	0.1700	0.0330	0.0755	0.3069	0.2314

Transportation & Utilities (mean (RS) = (0.184)). For most of the other economic sectors, the mean (ES) and (RS) measures do correspond to each other in a similar way. One major exception is Leisure & Hospitality, which in 1990 has a mean (ES) of (0.092), but a mean (RS) of just (0.038) in 1990. The difference in the two measures for this sector is very likely due to the fact that average earnings in the Leisure & Hospitality sector in 1990 were much lower than in the other sectors.

Looking at the mean (ES) and (RS) data for 2004 in Table 7, we find that there is again a close correspondence between the two measures—with Leisure & Hospitality again being the exception. In comparing the 2004 measures to the measures for 1990, however, there are some notable changes. For example, the Education & Health Services sector saw its mean (ES) grow from (0.099) in 1990 to (0.128) in 2004. This sector's mean (RS) also grew, from (0.102) in 1990 to (0.133) in 2004. Similarly, the mean (ES) for Professional & Business Services grew from (0.077) in 1990 to (0.102) in 2004, and its mean (RS) grew from (0.079) to (0.109) over the same period. These increases reflect the rise, during this period, of the Education & Health Services and the Professional & Business Services sectors.

Conversely, there were sectors that saw their mean (ES)s and (RS)s decline over this period. The sector that experienced the largest decline—by far—was Manufacturing, which saw its mean (ES) fall from (0.165) in 1990 to (0.120) in 2004 and its mean (RS) fall from (0.210) in 1990 to (0.159) in 2004. The second largest decline occurred in the Trade, Transportation & Utilities sector which saw its mean (ES) fall from (0.207) in 1990 to (0.195) in 2004 and its mean (RS) fall from (0.184) in 1990 to (0.170) in 2004.

Industrial Structure and Earnings Inequality

Having described the Theil, and the (ES) and (RS) measures for 1990 and 2004, section one concludes with an initial exploration of the association between the level of earnings inequality and the measures of industrial structure in both 1990 and 2004, with a focus on the financial services and information technology sectors. Presented in Table 8 are the bivariate correlations between the Theil and the (ES) and (RS)s for both years. Examining first the correlations for 1990, we observe that both the (ES) and (RS) measures for Finance and Information, rather than having a positive correlation with inequality—as suggested in the **second hypothesis**—appear to have a *negative* correlation. The correlation coefficients for the share measures for Information in 1990 are not, in any case, statistically significant. The one sector that does appear to have a statistically significant positive correlation with inequality in 1990—based on both the (ES) and (RS)—is Education & Health Services. Moreover, there are two other sectors—in addition to Finance—that appear to have a statistically significant *negative* association with inequality in 1990: Federal and State Government. Again this finding is based on both the (ES) and (RS) measures.

Table 8: Bivariate Correlations with Theil 1990 and 2004

Variable	*(r) ES 1990*	*(r) RS 1990*
Finance	-0.19***	-0.22***
Information	-0.03	-0.06
Manufacturing	0.10	0.26***
Professional & Business Services	-0.10	-0.06
Construction	0.04	0.02
Education & Health Services	0.21***	0.16**
Federal Government	-0.17***	-0.14**
State Government	-0.12*	-0.12*
Local Government	0.14**	0.04
Natural Resources & Mining	0.09	0.07
Leisure & Hospitality	-0.06	-0.21***
Other Services	0.07	-0.15**
Trade, Transportation, & Utilities	-0.06	-0.20***

	(r) ES 2004	*(r) RS 2004*
Finance	0.16***	0.31***
Information	0.21***	0.21***
Manufacturing	0.03	0.15**
Professional & Business Services	0.32***	0.29***
Construction	-0.07	-0.16***
Education & Health Services	0.02	-0.15**
Federal Government	-0.08	-0.10
State Government	-0.20***	-0.22***
Local Government	-0.04	-0.16***
Natural Resources & Mining	-0.09	-0.05
Leisure & Hospitality	-0.08	-0.15**
Other Services	0.12**	-0.14**
Trade, Transportation, & Utilities	-0.04	-0.18***

In terms of the correlations in 2004, it is clear from Table 8 that the relationship between the Finance and Information sectors—as well as some other economic sectors—and inequality had changed markedly over the 1990 to 2004 period. For example, by 2004 the (ES) and (RS) measures for Finance and Information had come—as hypothesized—to be positively correlated with inequality. In addition, while the Professional & Business Services sector had no discernible relationship with inequality in 1990, in 2004 this sector had a statistically significant positive correlation with inequality. Similarly, the

Education & Health Services sector went from having a positive correlation with inequality in 1990, to having a negative correlation in 2004—at least based on the (RS) measure.

In general, these correlation results offer further evidence—as first suggested in the review of the measures of industrial structure—of the significant structural changes that occurred in metropolitan economies between 1990 and 2004. These structural changes occurred as some industries grew in importance while others declined—and the industries associated with the level of inequality in each year also changed. Moreover, given that the nature of the inequality phenomenon appears to have changed so significantly between 1990 and 2004, it may not be useful to use the cross-sectional data to test the theoretical model reflected in the **second hypothesis**. It may, instead, be more fruitful to use the data on the *change* in inequality over the 1990 to 2004 period to test the proposed model. This is explored further in Section 2.

Section 2: The Growth of Earnings Inequality at the Metropolitan Level, 1990 to 2004

In the previous section, it was concluded that in terms of explaining the causes of earnings inequality, it made sense to focus on explaining the causes of the *growth* of inequality. This is chiefly due to the fact that the nature of the inequality phenomenon appears to have changed significantly over time, and therefore, any conclusions about a given year would not be generalizable to other years. In addition, in examining the change in inequality over the 1990 to 2004 period, versus the level in either year, we are essentially controlling for all of the possible factors leading up to 1990 which may have had an impact on the level of inequality in 1990 and 2004. This fact will make it possible to draw stronger conclusions about cause and effect.

To reiterate, Section 2 begins with a description of the *percent change* in inequality in metros over the 1990 to 2004 period. This is followed by a presentation of the annual time-series of inequality measures for metros over the period, which includes a comparison of the metro inequality measures to national level measures. Finally, the deconstructed Theil statistic is examined for the five metros with the highest rates of earnings inequality growth.

Based on the results of the metropolitan level inequality measures, it is found that of the 255 metro areas for which data were available, 205—or about 80 percent—experienced some degree of growth in earnings inequality between 1990 and 2004; whereas 50 metros—or about 20 percent—experienced some degree of decline. The rate of growth had a mean of 16.5 percent, a median of 11.4 percent, and a standard deviation of 23.3 percent. The highest rate of growth was 155.6 percent, (the Jersey City, NJ PMSA), while the highest rate of decline was -23.0 percent, (the Yuba City, CA MSA), for a range of 178.6 percent. Displayed in Figure 8 is a histogram showing the distribution of the rates of inequality growth for all 255 metro areas. The distribution shows a clear positive skew with a right-side tail. Presented in table 9 is a list of the top 20 metros with the highest rates of inequality growth.

The positive skew of the histogram in Figure 8 clearly demonstrates that while the vast majority of metros experienced some growth in earnings inequality over the 1990 to 2004 period, there was a relatively small subgroup for which inequality grew at particularly high rates. These 'high inequality growth metros' are represented by those regions where inequality grew at a rate of approximately 40 percent or higher—or at least one standard deviation above the mean of 16.5.[28] Moreover, within this group, (which totals 31 metros), there were five that had *extremely* high rates of earnings inequality growth—i.e. rates that were more than three standard deviations above the mean. Of these five metros, the top two were the Jersey City, NJ and Stamford-Norwalk, CT metros. These two metros had growth rates of 155.6 percent and 141.5 percent respectively—or rates that were more than five standard deviations above the mean. The next three highest metros were San Jose, CA; San Francisco, CA; and Ventura, CA; which had growth rates of 110.5 percent, 99.1 percent, and 89.8 percent respectively—or rates that were more than three standard deviations above the mean. In general, the results regarding the 31 high growth metros provides further evidence—as previously seen with the cross-

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[28] While designating those metros with inequality growth rates that are more than one standard deviation above the mean as 'high-inequality growth metros' may seem somewhat arbitrary, it should be noted that the great majority of metros with growth rates *below* the mean were within one standard deviation of the mean, or very close to it. In other words, the asymmetry in the distribution on the positive side begins with those metros with growth rates more than one standard deviation above the mean.

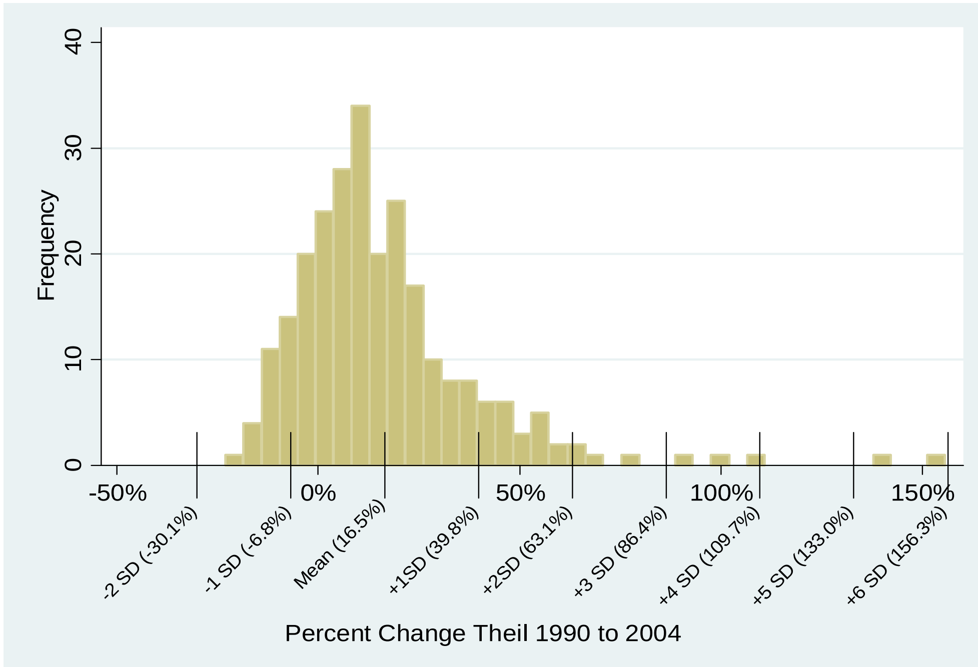

Figure 8: Histogram of Inequality Growth Rates 1990 to 2004 (all metros)

Table 9: Top 20 Metro Areas with Highest Inequality Growth Rates

Metro Name	% Change Theil 1990 to 2004
Jersey City, NJ	155.6%
Stamford-Norwalk, CT	141.5%
San Jose, CA	110.5%
San Francisco, CA	99.1%
Ventura, CA	89.8%
Middlesex-Somerset-Hunterdon, NJ	79.0%
Memphis, TN-AR-MS	66.4%
Hartford, CT	63.1%
Washington, DC-MD-VA-WV	62.6%
Charlotte-Gastonia-Rock Hill, NC-SC	61.2%
Austin-San Marcos, TX	58.2%
Bergen-Passaic, NJ	56.3%
Tacoma, WA	55.9%
Seattle-Bellevue-Everett, WA	55.4%
Los Angeles-Long Beach, CA	54.0%
Fayetteville-Springdale-Rogers, AR	53.1%
Newark, NJ	52.3%
Providence-Fall River-Warwick, RI-MA	52.1%
San Diego, CA	51.3%
New London-Norwich, CT-RI	47.7%

sectional inequality measures—in support of the **first hypothesis,** which argues that the growth of earnings inequality in the US over the 1990 to 2004 period was spatially concentrated within certain metropolitan regions.

Having identified the group of 31 metros with the highest rates of growth in earnings inequality, it will be useful to observe more closely how earnings inequality actually evolved in these regions over the 1990 to 2004 period, particularly in comparison to the remaining 224 metros. This can be done by simply constructing a time-series plot of the annual inequality measures for each metro for each year. Due to the fact, however, that it is not practical to present such a time-series plot for each of the 255 metros individually, each metro is first grouped according to its rate of growth in earnings inequality from 1990 to 2004. The mean Theil measure for each group of metros for each year is then calculated and plotted as a time-series.

We begin by focusing just on the 31 high-growth metros, dividing them into three groups: (1) metros with inequality growth rates between five and six standard deviations above the mean, (2) metros with growth rates between three and five standard deviations above the mean, and (3) metros with growth rates between one and three standard deviations above the mean. Presented in Figure 9 are the time-series plots of the mean Theil measures for each of these three groups for each year. We should note again that there are just 2 metros in group #1 and 3 metros in group #2. Also included in Figure 9 are the mean annual Theil measures for each year for all 255 metros combined.

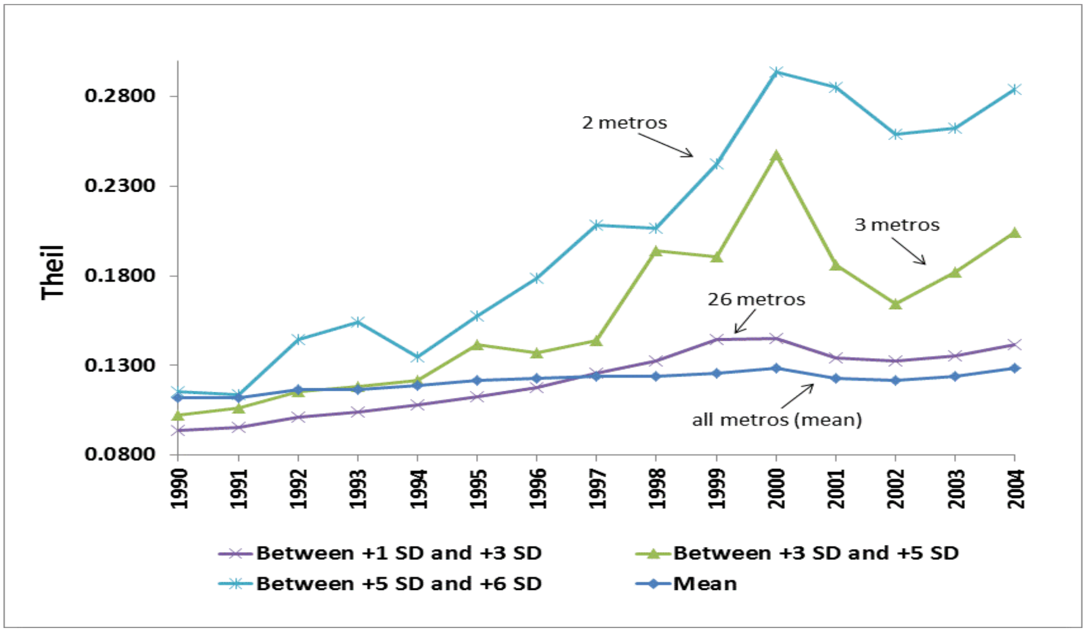

Figure 9: Mean Annual Theil Measures for Groups of Metros with High Inequality Growth Rates, Plus Mean Theil Measures for all Metros: 1990 to 2004.

Source: BLS data analyzed by author

There are a number of things worth noting about Figure 9. First, the graph again demonstrates that there are five metros that experienced *extremely* high rates of earnings inequality growth over the period, compared to the rest of the population of metros. Moreover, while earnings inequality for these top five metros peaked in 2000--the last year of the economic expansion of the 1990s--and then dropped sharply over the following few years of recession and early recovery, by 2003 and 2004, earnings inequality began to grow again. By 2004, inequality in the top two metros had almost reached their previous peak. In terms of the group of 26 metros, earnings inequality, by comparison, does not appear to have grown very rapidly for these metros. This is due, however, to the extremely high growth rates of the top five metros. If the scale used to plot the inequality measures is reduced, moreover, the significant growth of earnings inequality in the group of 26 metros becomes much clearer.

Presented in Figure 10 is a recreation of the time-series plot for the 26 metros along with the mean Theil measures representing the remaining 224 metros as divided into two groups: (1) metros with growth rates between one standard deviation above the mean and one standard deviation below the mean, and (2) metros with growth rates more than one standard deviation below the mean. The graph does clearly demonstrate the significant

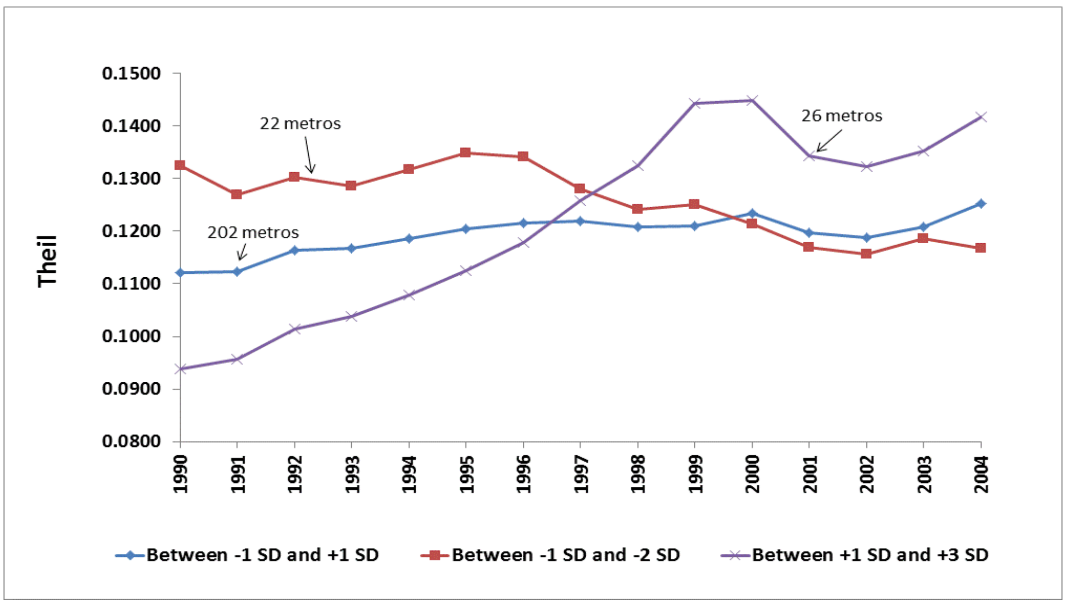

Figure 10: Mean Annual Theil Measures for Groups of Metros with High, Low, and Negative Inequality Growth Rates, Plus Mean Theil Measures for all Metros: 1990 to 2004

Source: BLS data analyzed by author

growth of earnings inequality in the 26 metros, particularly in comparison to the other two groups. It is interesting to note, however, that the high rates of growth in the 26 metros is in part due to the fact that their initial level of earnings inequality in 1990 was much lower than the other two groups.

The Growth of Earnings Inequality at the National Level

Having reviewed the time-series measures of earnings inequality at the metro level, we will briefly compare these measures to measures at the national level. As noted in Chapter 4, national measures of earnings inequality can be calculated using the same method as that used to calculate the metro-level measures: where the between group component of the Theil statistic is applied to employment and earnings data grouped at the 6-digit NAICS level. The only difference is that *national* level data are used instead of metro level data. Again, because the grouping structure used to calculate the Theil statistic at the national level—the 6-digit NAICS—is the same as that used at the metro level, the results are directly comparable.

Applying this method at the national level, it is found that for the nation overall, earnings inequality over the 1990 to 2004 period grew at a rate of 40.5 percent. This rate is considerably higher than the mean or median growth rates at the metro level, which were 16.5 percent and 11.5 percent respectively. There was, however, a small group of metros—29 in total—where inequality grew at a faster rate than at the national level. Not surprisingly, this group of 29 metros is virtually identical to the group of the 31 'high-growth' metros just highlighted; although two of the 31 high-growth metros had growth rates that were a bit lower than the rate at the national level. To help visualize the comparison of the metro versus national level inequality measures, Figure 11 shows the annual time-series measures of earnings inequality at the national level compared to the mean growth rate for the group of 31 high-growth metros, along with the mean growth rate for all metros. The graph shows a similar pattern of earnings inequality growth at the national level compared to the growth for the 31 high growth metros. The key difference is simply the rate of growth, which was higher for the 31 metros than it was at the national level. This result offers strong evidence that the rate of growth of earnings inequality in the U.S. over the 1990 to 2004 period was—as suggested in the **first hypothesis**—higher in a relatively small group of specific metro areas than it was at the national level.

In addition, it should be noted that in terms of comparing the *levels* of inequality at the national versus metro levels, the vast majority of metros had levels of inequality that were higher than the nation overall. In fact, a total of 229 metro areas had levels of inequality in 1990 that were higher than at the national level. Things had changed significantly by 2004, however, where far fewer metros—129 in total—had levels of inequality that were higher than at the national level.[29]

[29] It is not clear why such a large number of metros—in both years—have levels of inequality that are higher than the nation overall. It might be assumed that because the national measures include data from low-wage rural areas—and the metro data do not—inequality at the national level would be higher than in most metros.

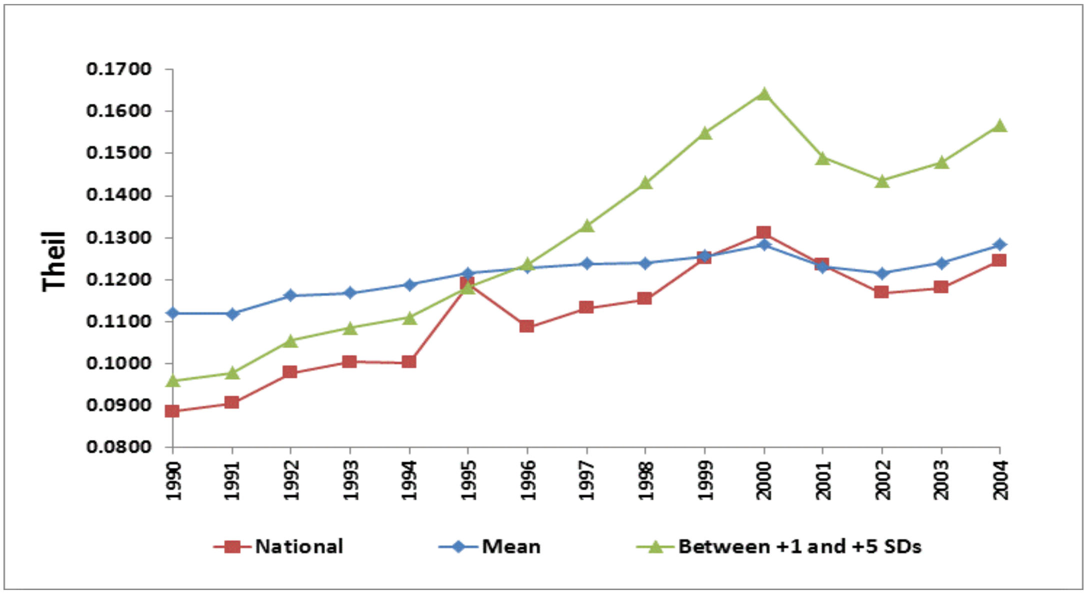

Figure 11: Annual Theil Measures for U.S. Versus Mean Annual Theil Measures for Group of Metros with High Inequality Growth Rates, Plus Mean Theil Measures for all Metros: 1990 to 2004

Source: BLS data analyzed by author

Deconstruction of the Theil Statistic

Next, we can begin to get a sense of the role of industrial structure generally, and the financial services and information technology sectors in particular, in the growth of earnings inequality in metros if we take advantage of the 'deconstructible' property of the Theil statistic. As described in Chapter 4, the between groups component of the Theil statistic for a given metro in a given year can be deconstructed such that it is possible to observe the contribution of each industrial sector in that metro to the level of inequality in a given year. To reiterate, the between groups component of the Theil statistic takes the form:

$$[1] \quad T' = \sum_{i=1}^{n} \left(\frac{p_i}{P} \right) \left(\frac{Y_i}{Y} \right) \log \left(\frac{Y_i}{Y} \right)$$

where *pi* is total employment in industrial group *i*, *P* is total employment for all industrial groups combined, *Yi* is average earnings for industrial group *i*, and Y is average earnings for all industrial groups combined. The term inside the summation sign—referred to as the Theil element—reflects the contribution of each industry to the level of earnings inequality in a metro in a given year.

Presented here is the deconstructed Theil statistic for the top five metros with the highest rates of earnings inequality growth over the 1990 to 2004 period. These top five metros include: Jersey City, NJ; Stamford-Norwalk, CT; San Jose, CA; San Francisco, CA; and Ventura, CA. We begin with the Jersey City, NJ metro. Pictured in Figure 12 are the annual Theil elements for the three industrial sectors in the Jersey City metro with the largest point increases in their Theil elements over the 1990 to 2004 period. Also pictured is the mean Theil element for each year for all industries combined. The graph clearly demonstrates the dominant role of the Finance and Insurance industry in the growth of earnings inequality in the Jersey City metro. While the two sectors--Management of companies and enterprises, and Information--also made contributions, these were very small compared to the contribution of Finance and Insurance.

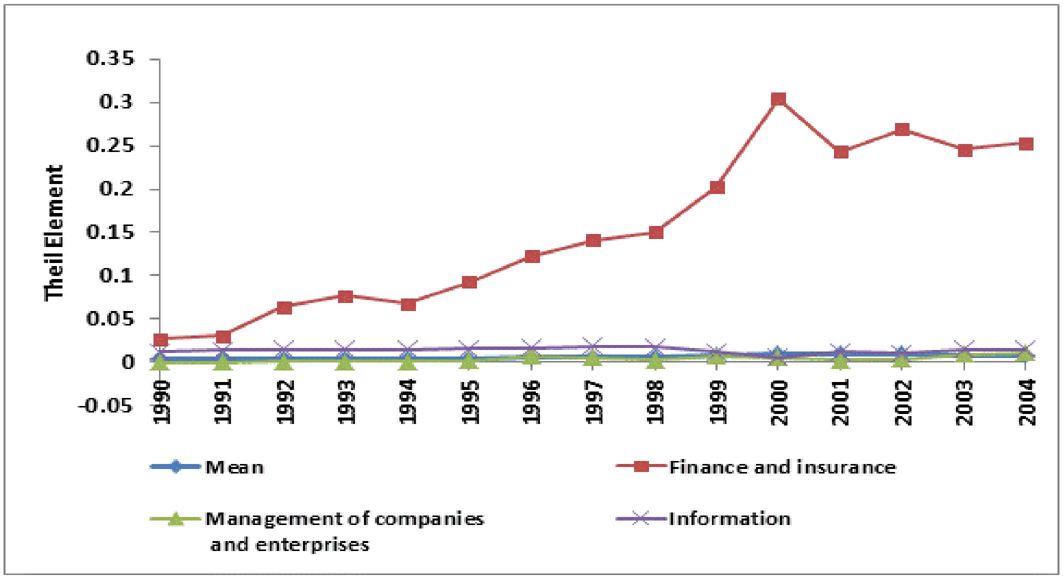

Figure 12: Annual Theil Elements, Top 3 Industrial Sectors and Mean, Jersey City, NJ PMSA

Source: BLS data analyzed by author

Next, pictured in Figure 13 are the annual Theil elements over the 1990 to 2004 period for the top three industrial sectors in the Stamford-Norwalk, CT metro, along with the mean Theil element. As was the case in the Jersey City metro, the dominance of the Finance and Insurance industry in the growth of earnings inequality over the period is clear. While the Management of companies and enterprises sector also made some contribution to the level and growth of earnings inequality over the period, in comparison to the Finance and Insurance sector, its contribution was minor.

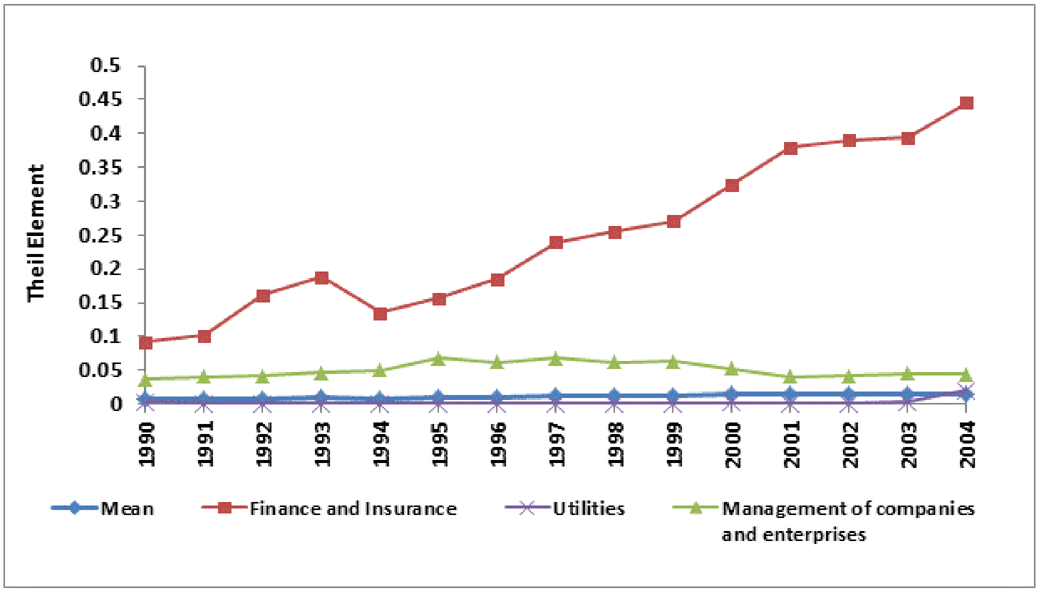

Figure 13: Annual Theil Elements, Top 3 Industrial Sectors and Mean, Stamford-Norwalk PMSA

Source: BLS data analyzed by author

Pictured in Figure 14 are the annual Theil elements for the top three sectors in the San Jose metro area, and the mean. In this case, the results are quite different from the previous two metros. The Finance and insurance sector does not appear on the graph, indicating that it is not in the top three industries in terms of contributing to the growth of earnings inequality. Instead, the Information sector made the largest contribution to the *growth* of earnings inequality over the 1990 to 2004 period. Also important, moreover, was the Professional and Technical Services sector, which made significant contributions to both the growth and level of earnings inequality over the period.

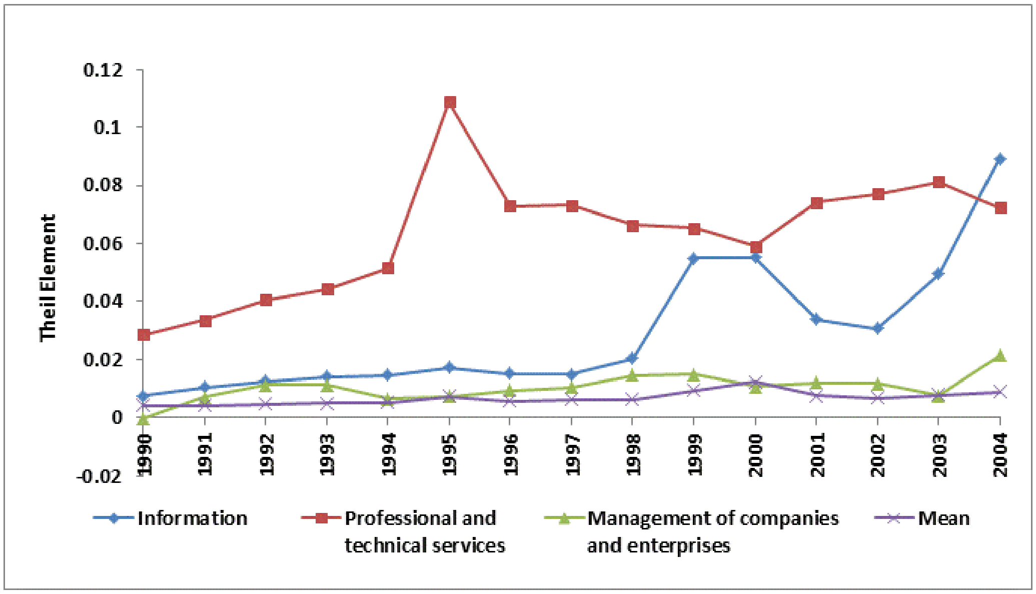

Figure 14: Annual Theil Elements, Top 3 Industrial Sectors and Mean, San Jose PMSA

Source: BLS data analyzed by author

Presented in Figure 15 are the Theil elements for the top three sectors in the San Francisco, CA metro, and the mean. As was the case in the Jersey City and Stamford-Norwalk metros, the Finance and insurance industry made the most significant contribution to the growth of earnings inequality over the period. As was the case in the San Jose metro, the Information sector also made a significant contribution to inequality growth. While the Professional and technical services sector also made a contribution, this was more to the *level* of earnings inequality over the period, rather than to its growth.

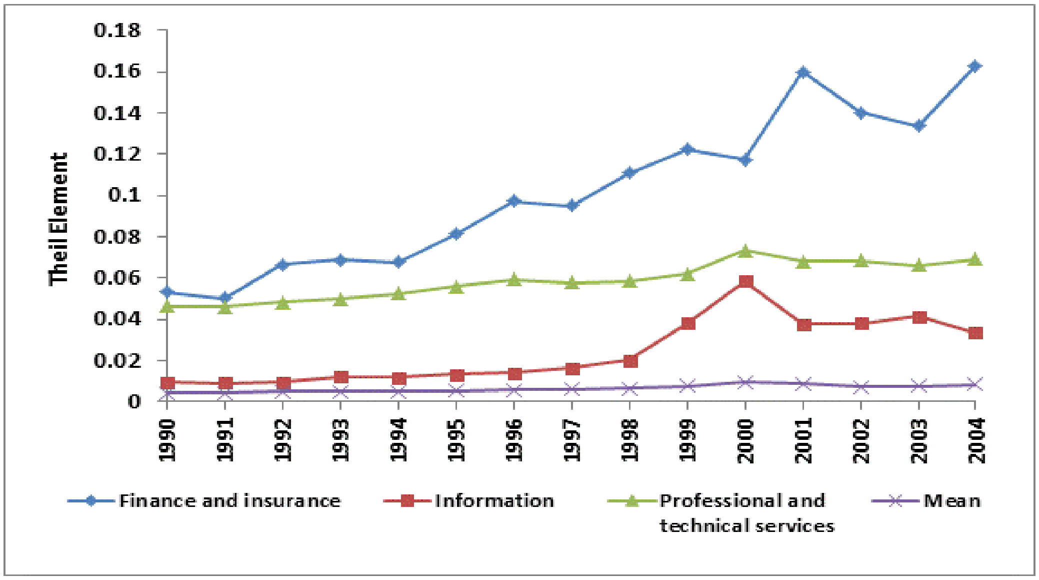

Figure 15: Annual Theil Elements, Top 3 Industrial Sectors and Mean, San Francisco PMSA

Source: BLS data analyzed by author

Finally, pictured in Figure 16 are the top three Theil elements for the Ventura, CA metro area, along with the mean. In this case, the Manufacturing sector made the most important contribution to the growth of earnings inequality over the 1990 to 2004 period. This makes Ventura unique in comparison to the other four high inequality growth metros. Also unique to Ventura was the role of the Wholesale trade sector to the growth of earnings inequality. It is also true, however, that the Finance and insurance sector, as in most of the other metros, made a significant contribution to the growth of inequality.

In general, examining the Theil elements for the top five metros does offer some important initial insights—at least in the metros with extremely high earnings inequality growth rates—into the role of different sectors in the growth of earnings inequality. The importance of *Finance and Insurance* in each of these metros—with the exception of San Jose—is clear. The *Information* sector also made significant contributions in both the San Jose and San Francisco metros. The *Management of companies and enterprises* also had a role—albeit minor—in the growth of earnings inequality in both the Stamford-

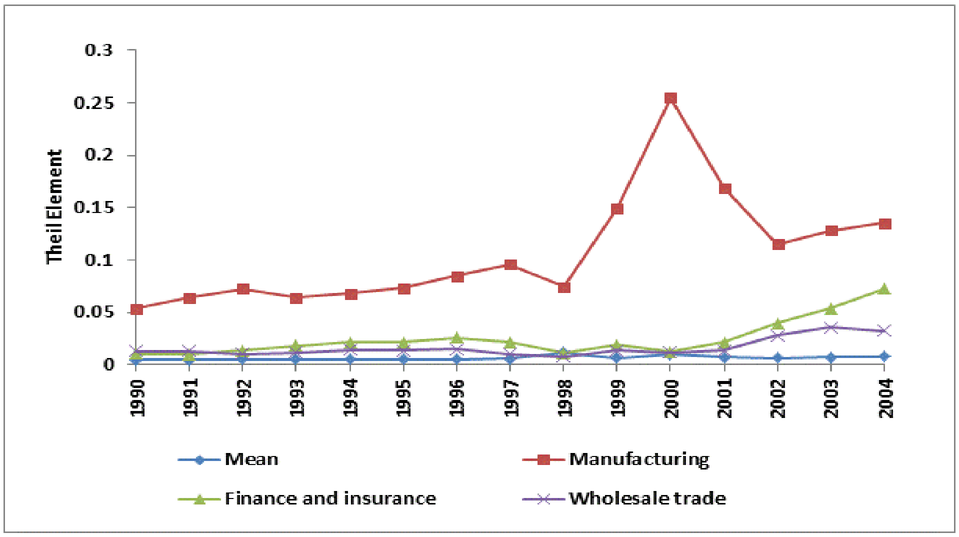

Figure 16: Annual Theil Elements, Top 3 Industrial Sectors and Mean, Ventura PMSA

Source: BLS data analyzed by author

Norwalk and San Jose metro areas. This certainly provides some initial support for the **second hypothesis** regarding the central role of the Finance and Insurance and Information sectors in the growth of earnings inequality in metro areas. We do not know, however, whether these insights regarding the extremely high inequality growth metros holds true for other metros. To further test the second hypothesis, therefore, more comprehensive quantitative statistical analysis is needed. This is the focus of the next section.

Section 3: Industrial Structure and the Growth of Metropolitan Earnings Inequality, 1990 to 2004

In Section three, the statistical relationship between the measures of change in industrial structure—with a focus on the financial services and information technology industries—and the changes in earnings inequality for *all* metros areas is explored. As already noted, this examination includes bivariate measures of correlation as well as a more formal quantitative model based on OLS regression. The regression model provides a more rigorous test of the **second hypothesis** regarding the relationship between the growth of earnings inequality and the growth of the financial services and information technology industries.

We begin with a description of the change in the industrial structure measures. Presented in Table 10 are the basic descriptive statistics for the change in (ES) and (RS)s for each sector, as well as the percent change in the Theil and the control variables that are later used in the regression model. In terms of the change in the (ES) and (RS) measures, we observe once again—as was found when examining the cross-sectional data—that the Professional and Business Services and Education & Health Services sectors grew the most over this period, while Manufacturing and Trade, Transportation, and Utilities sectors declined the most. It is also clear that the change in the (ES) and (RS)s, are highly correlated with each other.

Table 10: Descriptive Statistics, Change in Theil, Employment and Earnings Shares, 1990 to 2004

Change Theil 1990 to 2004	n	Mean	Median	Std. Dev.	Min	Max	Range
Percent Change Theil	255	16.5%	11.4%	23.3%	-23.0%	155.6%	178.6%
Point Change Theil	255	0.0164	0.0129	0.0248	-0.0321	0.2197	0.2518
Change Employment Shares 1990 to 2004							
Change ES Finance	255	0.0007	0.0001	0.0116	-0.0648	0.0834	0.1482
Change ES Information	255	-0.0021	-0.0023	0.0076	-0.0339	0.0417	0.0756
Change ES Manufacturing	255	-0.0471	-0.0444	0.0341	-0.1657	0.0371	0.2028
Change ES Prof & Bus Services	255	0.0258	0.0247	0.0183	-0.0378	0.1447	0.1825
Change ES Construction	255	0.0062	0.0056	0.0107	-0.0383	0.0474	0.0857
Change ES Educ & Hlth Services	255	0.0296	0.0273	0.0175	-0.0180	0.1160	0.1340
Change ES Federal Government	255	-0.0093	-0.0044	0.0157	-0.1305	0.0299	0.1604
Change ES State Government	255	-0.0025	-0.0016	0.0129	-0.0810	0.0314	0.1124
Change ES Local Government	255	0.0064	0.0057	0.0161	-0.0347	0.1712	0.2059
Change ES Natural Res & Mining	255	-0.0047	-0.0015	0.0110	-0.0588	0.0409	0.0997
Change ES Leisure & Hospitality	255	0.0094	0.0087	0.0146	-0.0755	0.1201	0.1956
Change ES Other Services	255	-0.0005	-0.0008	0.0066	-0.0345	0.0187	0.0532
Change ES Trade, Transp, & Util	255	-0.0121	-0.0132	0.0177	-0.0816	0.0433	0.1249
Change Earnings Shares 1990 to 2004							
Change RS Finance	255	0.0118	0.0082	0.0233	-0.0839	0.2204	0.3043
Change RS Information	255	-0.0010	-0.0019	0.0123	-0.0524	0.0741	0.1265
Change RS Manufacturing	255	-0.0519	-0.0504	0.0425	-0.1860	0.0606	0.2466
Change RS Prof & Bus Services	255	0.0299	0.0267	0.0271	-0.0665	0.2097	0.2762
Change RS Construction	255	0.0045	0.0052	0.0121	-0.0469	0.0541	0.1010
Change RS Educ & Hlth Services	255	0.0310	0.0289	0.0210	-0.0204	0.0967	0.1171
Change RS Federal Government	255	-0.0082	-0.0037	0.0183	-0.1243	0.0442	0.1685
Change RS State Government	255	-0.0041	-0.0024	0.0152	-0.0734	0.0639	0.1373
Change RS Local Government	255	0.0036	0.0025	0.0171	-0.0561	0.1301	0.1862
Change RS Natural Res & Mining	255	-0.0044	-0.0013	0.0109	-0.0796	0.0401	0.1197
Change RS Leisure & Hospitality	255	0.0094	0.0087	0.0146	-0.0755	0.1201	0.1956
Change RS Other Services	255	-0.0005	-0.0002	0.0047	-0.0298	0.0123	0.0421
Change RS Trade, Transp, & Util	255	-0.0138	-0.0123	0.0229	-0.1177	0.0466	0.1643
Control Variables							
Percent Change Population	255	19.5%	17.1%	16.3%	-10.0%	120.6%	130.6%
Average Share Black	255	0.1103	0.0709	0.111 1	0.0015	0.4843	0.4827
Average Share Hispanic	255	0.1031	0.0401	0.1521	0.0051	0.9424	0.9373
Change Share Black	255	0.0066	0.0043	0.0140	-0.0435	0.0753	0.1188
Change Share Hispanic	255	0.0388	0.0271	0.0357	0.0016	0.1714	0.1698
Average Share Bachelors	255	0.1427	0.1375	0.0419	0.0663	0.2882	0.2219
Average Share Masters	255	0.0683	0.0620	0.0258	0.0299	0.1834	0.1535
Average Share Doctorate	255	0.0100	0.0070	0.0094	0.0018	0.0564	0.0546
Change Share Bachelors	255	0.0228	0.0223	0.0119	-0.0066	0.0622	0.0688
Change Share Masters	255	0.0127	0.0123	0.0073	-0.0059	0.0424	0.0483
Change Share Doctorate	255	0.0020	0.0018	0.0019	-0.0070	0.0139	0.0208

Finally, the statistical relationship between the changes in the (ES) and (RS) measures for the financial services and information technology industries—as well as the other industrial sectors—and the change in earnings inequality is explored. Presented in Table 11 are the bivariate correlations between the percent change in the Theil from 1990 to 2004, and the change in the (ES) and (RS)s for each economic sector. In terms of comparing the correlations for the change in (ES)s versus the (RS)s, it is clear that the change in (RS) measures generally have stronger and more statistically significant correlations with the percent change in the Theil than do the change in (ES) measures. Of the change in (RS) measures, the variable with the strongest positive, statistically significant correlation is the change (RS) Finance (r = 0.49), followed by change (RS) Professional & Business Services (r = 0.22), and change (RS) Information (r = 0.18). Conversely, the variables with the strongest negative, statistically significant correlation was change (RS) Trade, Transportation, & Utilities (r = -0.28), Change (RS) Education and Health Services (r = -0.26), and Change (RS) Construction (r = -0.22).

Table 11: Bivariate Correlations with Percent Change in Theil

	Change ES	*Change RS*
Finance	0.14**	0.49***
Information	0.07	0.18***
Manufacturing	-0.16***	-0.06
Professional & Business Services	0.13**	0.22***
Construction	-0.06	-0.17***
Education & Health Services	-0.03	-0.26***
Federal Government	-0.08	-0.07
State Government	-0.03	-0.02
Local Government	0.13**	-0.01
Natural Resources & Mining	0.13**	0.02
Leisure & Hospitality	0.05	-0.10^
Other Services	0.15**	-0.07
Trade, Transportation, & Utilities	-0.10^	-0.28***

The results for the change in (RS) measures do provide initial support for the hypothesized positive relationship between the growth of the financial services and information technology industries and the growth of earnings inequality in metropolitan areas. The results also suggest, however, that the growth of the professional and business services sector was also positively associated with the growth of earnings inequality, and in fact, this sector may be more important in explaining the growth of earnings inequality than the information technology sector. In addition, the results in Table 11 suggest that some sectors may be associated with *declining* earnings inequality, including the Trade, Transportation, & Utilities; Education & Health Services; and Construction sectors.

Next, to provide a more rigorous test of the hypothesized relationship between industrial structure and inequality generally—and the relationship between the Finance and Information sectors and inequality specifically—OLS regression analysis is utilized. Moreover, it is clear from the correlation results in Table 11 that the change in (RS) variables—versus the change in (ES) variables—have the most promise in terms of explaining the growth of earnings inequality and thus providing a test of the theoretical model. For this reason, the change in (ES) variables are not included the OLS regression.

In the regression model, the Percent Change in Theil is the dependent variable and the Change in (RS) for each of the economic sectors are the independent variables. The choice of which of the 13 economic sectors to include in the model is based on a process of adding variables to the model one at a time, and keeping only those variables that clearly increase the R-square. Using this method, 6 sectors are included in the model: Change (RS) Construction, Change (RS) Finance, Change (RS) Information, Change (RS) Professional and Business Services, Change (RS) Education and Health Services, and Change (RS) Trade, Transportation, and Utilities. In addition to adding to the R-square, these 6 sectors also have statistically significant bivariate correlations with the percent change in Theil, as displayed in Table 11.

Model 1 of Table 12 presents the regression results with the six economic sectors included. All six variables are significant at the 90 percent confidence level or higher. The Change (RS) Finance variable has the largest positive coefficient (4.71), followed by Professional & Business Services (2.03), and Information (1.80). Construction has the largest negative coefficient (-2.74), followed by Trade, Transportation, and Utilities (-1.40), and Education and Health Services (-1.16). The adjusted R-squared for this model is (0.37), which means that together these 6 variables explain 37 percent of the variability in the change of earnings inequality over the 1990 to 2004 period.

There is an important issue of correctly interpreting the coefficients of the regression model, because the independent variables, as well as being bounded individually (-1 to

Table 12: Percent Change in Theil, 1990 to 2004, and Change in Earnings Shares

	Model 1	Model 2
Change RS Construction	-2.74*** (0.96)	-1.64* (0.98)
Change RS Education	-1.16* (0.60)	-0.90^ (0.60)
Change RS Finance	4.71*** (0.53)	3.76*** (0.51)
Change RS Information	1.80* (0.96)	-0.00 (0.90)
Change RS Professional & Business Services	2.03*** (0.46)	1.43*** (0.45)
Change RS Trade,Transp & Utilities	-1.40** (0.53)	-0.86* (0.49)
Percent Change Population		-0.20** (0.08)
Average Share Black		0.40*** (0.12)
Average Share Hispanic		0.29*** (0.10)
Change Share Black		-1.88** (0.90)
Change Share Hispanic		0.55 (0.44)
Average Share Bachelors		1.59*** (0.48)
Average Share Doctorate		-5.63*** (1.63)
Change Share Bachelors		-0.72 (1.41)
Change Share Masters		4.90** (2.25)
Change Share Doctorate		16.35** (6.62)
Intercept	0.08 (0.03)	-0.19*** (0.06)
N	255	255
Adj. R-squared	0.37	0.49

1), are also bounded as a group. For a given metro area, the sum of the Change in (RS)s for all 13 sectors combined will always be zero. Therefore, any increase in the share for one sector has to be reflected in a commensurate decrease in the share for one or more of the other sectors. For the regression results in model 1 of Table 12, therefore, the 7 sectors omitted from the model act, as a group, as a dummy variable. The coefficients in the regression are, therefore, interpreted relative to the group of omitted variables.

It is of course important to add some control variables to model 1 to see what effect they have on the significance of the economic variables. As previously noted, the literature on income and earnings inequality typically includes demographic variables as possible explanations for inequality; among these are, skill level, racial composition, and population size/growth. As previously listed and explained in Chapter 4, Table 13 presents the specific control variables added to the model, along with measures of their correlations with the percent change in Theil. For the race and education variables, *average* proportions (based on the 1990 and 2004 data combined) are included in the

Table 13: Control Variables, Bivariate Correlations with Percent Change in Theil

Variable	(r)
Percent Change Population (1990 to 2004)	0.01
Average Proportion Black (1990 and 2004)	0.09^
Average Proportion Hispanic (1990 and 2004)	0.12*
Change Proportion Black (1990 to 2004)	-0.13**
Change Proportion Hispanic (1990 to 2004)	0.13**
Average Proportion Bachelors (1990 and 2004)	0.36***
Average Proportion Masters (1990 and 2004)	0.33***
Average Proportion Doctorate (1990 and 2004)	0.01
Change Proportion Bachelors (1990 to 2004)	0.18***
Change Proportion Masters or Professional (1990 to 2004)	0.41***
Change Proportion Doctorate (1990 to 2004)	0.20***

model, as well as the *change* in proportions from 1990 to 2004. The Average Proportion Masters variable was dropped because it was causing significant multi-collinearity in the model.

Presented in model 2 of table 12 are the regression results with the control variables included. It is observed that Information is no longer significant. This occurs once one or more of the education variables are added to the model. The economic variables that remain clearly significant, with the controls added, are Change (RS) Finance and Change (RS) Professional & Business Services. In addition, a number of the control variables themselves are significant, including: Percent Change Total Population, Average Proportion Black, Average Proportion Hispanic, Change Proportion Black, Average Proportion Bachelors, Average Proportion Doctorate, Change Proportion Master, and Change Proportion Doctorate.

The results of model 2 provide strong evidence that the change in the size of the Finance sector in a metro area, as measured by the change in its share of total earnings in that metro, *does* have a strong positive association with the percent change of earnings inequality in that metro area. This is true even when controlling for population, race, and education. In terms of the Information sector, however, once the education variables are controlled for, growth in this industry does not appear to have a statistically significant positive association with the growth in earnings inequality. What was found instead was that the growth of the Professional and Business Services industry appears to have a strong positive association with the growth of earnings inequality. In addition, an increase in the size of either the Construction or Trade, Transportation, and Utilities industries has a *negative* association with the growth in earnings inequality, though only at the 90 percent confidence level. Again, this is true even when controlling for population, race, and education.

Conclusion

The empirical results presented in this Chapter do generally provide strong support for the **first hypothesis**. The cross-sectional, change, and time series measures of earnings inequality clearly reflect the changing spatial dynamics of earnings inequality in US metro areas over the 1990 to 2004 period. The growth of earnings inequality, while widespread across metros, was much stronger in a relatively small number of metro areas. For a number of these metro areas—29 in total—the rate of inequality growth was higher than it was at the national level over the same period.

In terms of the **second hypothesis**, the deconstructed Theil statistic for the five metros with the highest inequality growth rates does demonstrate the important role of both the Finance and Insurance, and Information sectors in the growth of earnings inequality in those metros. The results from the OLS regression model also provide strong evidence, for the 255 metro areas generally, of a statistically significant and substantial positive correlation between the financial services industry—and specifically its growth—and the growth of earnings inequality. However, the regression results for the information technology industry are not clear. When controlling for educational attainment, there is in fact no statistically significant relationship between the growth of this industry and the growth of earnings inequality. There was instead evidence of a positive and statistically significant relationship between the growth of the professional and business services industry and the growth of earnings inequality in metro areas over the 1990 to 2004 period.

CHAPTER 6: CONCLUSIONS & POLICY RECOMMENDATIONS

Introduction

This final chapter reviews the empirical results of the study and their implications for theory and public policy. The areas of public policy to be reviewed include the federal income tax, financial regulation, and corporate governance. The chapter concludes with a short discussion of directions for future research.

Empirical Conclusions

As discussed at the end of the previous chapter, the research presented here offers two major empirical findings. First, it was found that while earnings inequality grew in the great majority of metro areas in the US over the 1990 to 2004 period, the *rate* of growth varied considerably and was much higher for a relatively small number of metros. This finding, in general, represents a confirmation of the **first hypothesis**, which had suggested that the growth of earnings inequality in the US was spatially concentrated. Second, it was found that the growth of earnings inequality in metros was in part driven by the growth of the financial services and professional & business services industries. This result, in fact, represents only a partial confirmation of the **second hypothesis**, which had suggested that the growth of earnings inequality in metros was driven by the growth of the financial services and information technology industries. When controlling for the levels of educational attainment, however, no clear role for information technology was found. It was instead found that the professional & business services industry—in addition to the financial services industry—had contributed to the growth of earnings inequality over the 1990 to 2004 period.

While the evidence is clear regarding the contribution of the financial services and professional & business services industries to the growth of earnings inequality in metro areas, there was nevertheless a significant amount of unexplained variance in the final regression model (adjusted R-squared = 0.49). There are a number of possible explanations for this result. One explanation relates to the fact that the employment and earnings data used to measure industrial structure were highly aggregated, where just thirteen industrial sectors represented an entire metro economy. Moreover, any significant shifts in employment or wages which occurred *within* one or more of these broad sectors—shifts which may have had an impact on earnings inequality—is simply not accounted for. Measures of industrial structure based on employment and earnings data aggregated at lower levels—such as at the 2 or 3-digit NAICS level—may have been able to explain more of the total variance in the regression model. Aside from the measures of industrial structure, another possible reason for the large unexplained variance in the model is that important explanatory variables were omitted from the model. There are, for example, additional demographic variables—such as gender, immigration, and age—that, if included, might have improved the explanatory power of the model.

Implications for Theory

To reiterate, the theoretical model proposed in Chapter 3 began with the taxonomy of industrial structure developed by Galbraith (1998) and Galbraith and Berner (2001), which divides the economy into three sectors, including: the S-Sector, S standing for services; the C-Sector, C standing for consumption goods; and the K-sector, K standing for knowledge or capital goods. Building on this taxonomy, the proposed model added an additional sector, the F-Sector, F standing for financial services. Average wages for workers in both the K and F sectors are high relative to the C and S sectors because firms in these industries operate with a high degree of monopoly power, and a portion of the monopoly profits earned as a result are shared with workers in the form of high earnings. With the F-K-C-S taxonomy in mind, it was then hypothesized that metropolitan economies which experienced a significant growth in earnings inequality over the 1990 to 2004 period had large and rapidly growing K and/or F sectors. It was the growth of these two sectors, moreover, that drove the increases in earnings inequality. In the statistical analysis which followed, the K sector was represented by the information technology industry, and the F sector—quite obviously—by the financial services industry.

The empirical results of this research do not, in fact, correspond precisely to the theoretical model proposed. While the evidence for the F-sector is clear, the results for the K-sector are at best inconclusive.[30] The positive results for the professional & business services sector, moreover, were not predicted by the model, as this sector was not included in the original F-K-C-S taxonomy. The result for the professional & business services sector may in fact correspond better to Institutional explanations of inequality, rather than post-Keynesian. As discussed in Chapter 2, one of the Institutional explanations for growing earnings inequality in the U.S concerns changes in the nature of corporate governance, where control over the management of corporations has shifted from stockholders (the owners of capital), to executive managers. With effective control over the corporation, moreover, executives have been essentially able to set their own pay, choosing to increase it significantly through growing salaries, bonuses, and stock options. (Galbraith, 2004, pp. 18-19) One of the results of this development has been a steady increase in earnings or pay inequality within corporations between executives and average workers.

There is good reason to believe, in fact, that the finding regarding the contribution of the professional and business services industry to the growth of earnings inequality in metro areas is in part due to these changes in corporate governance in the US. This is because the growth of average earnings for corporate executives should be reflected in the employment and earnings data for the 2-digit NAICS Sector: 55 Management of Companies and Enterprises. This 2-digit sector, moreover, is a subsector of the NAICS Supersector: Professional and Business Services, the data for which were used to

[30] One possible explanation for this is that the information technology sector is not an adequate representation of the K-sector, as significant parts of the K-sector may fall into one of the other Supersector categories.

calculate the measures of industrial structure for that sector. Thus, any significant increases in executive pay would have a direct impact on the contribution of the professional and business services sector to the growth in earnings inequality.

Implications for Public Policy

Income Tax Policy

In terms of economic policy, one of the most direct macro-policy options available to address overall income inequality in the U.S. is income tax policy, and specifically, the federal income tax. By simply increasing the marginal tax rates for individuals with high incomes, you can directly reduce the overall level of income inequality in the country. According to the Economic Policy Institute (EPI) in Washington, D.C., a sharp reduction in effective federal tax rates for the richest 1% of taxpayers in the U.S. has contributed to a rise in income inequality since 1979. This tax cut has occurred while the effective tax rate for a middle-class family of four has changed little since 1980. (Mishel et al., 1998, p. 4) Similarly, a study by the Congressional Budget Office on income and tax trends since 1979 in the U.S. found that the percentage of income that Americans pay in federal taxes declined between 1979 and 2001 among every income group, but that households in the top 1 percent of the income distribution had the largest percentage-point fall in effective tax rates. (US CBO, 2001)

Financial Regulation

The financial crisis in the U.S. in 2007-2008, and the Great Recession which followed, have certainly served to highlight the continuing problems of instability and speculative excess in the U.S. financial system.   Many observers, such as Crotty (2009) and Kuttner (2009), have argued that the recent financial crisis was the inevitable result of the deregulation of finance in the U.S., which began in the late 1970s, as well as the lack of new regulations designed to keep up with rapid changes in the financial services industry. It was deregulation and the lack of adequate new regulation, moreover, that allowed for the increases in system-wide leverage and unchecked financial innovations, both of which helped fuel the cycles of speculative boom and bust in the U.S financial markets since the 1980s.

In addition to creating instability, a number of observers—such as former FDIC chairwoman Sheila Bair—have argued that the overly speculative nature of U.S. financial markets have also allowed the markets and the financial services industry to become inefficient and overly large. As we have seen in the results of the research presented here, moreover, an overly large financial services industry in the U.S. is itself problematic in that it has contributed significantly to the growth of earnings inequality in the country. For this reason, in addition to preventing another financial crisis, it is argued here that the proper regulation--and re-regulation--of the financial services industry in the U.S. could help reduce its size and thereby reduce the problem of earnings inequality.

In terms of financial regulatory policy in the U.S., the Dodd-Frank Wall Street Reform and Consumer Protection Act, passed in July 2010 in response to the U.S. financial crisis, does lay out a broad framework for financial regulatory reform. It also, however, leaves a number of the important details of rulemaking and implementation to various regulators, and the final set of rules will not be implemented for many years to come. (Epstein and Pollin, 2011, pp. 1-3) The new law has also been criticized for not adequately dealing with the "too big to fail" phenomenon. This refers to the problem where specific financial institutions are so large that their failure poses a systemic risk to the financial system. It was this risk, moreover, that required the taxpayer-funded bailouts of many of the largest financial institutions during the financial crisis. (Wilmarth, 2011, p. 954)

There are provisions of the Act, however, which have the potential to reduce the overly-speculative nature of financial markets and institutions in the U.S. One example is the so-called "Volker rule." This is a set of measures designed to prevent proprietary trading by insured commercial banks, as well as to limit such trading by non-bank financial institutions such as hedge funds and private equity firms. Curbing or prohibiting proprietary trading is important as the practice presents a conflict of interest, as banks were able to use information on the trading patterns of their clients to inform their decisions about trading for their own portfolio. In addition, proprietary trading was mainly funded with short-term borrowing backed up by risky collateral, and thus had a role in inflating the speculative bubble. (Epstein and Pollin, 2011, p. 5)

Another important provision of Dodd-Frank concerns the major private credit rating agencies—Moody's, Standard & Poor's, and Fitch—which were also seen as having contributed to the financial bubble. The rating agencies were designed to provide financial markets with objective and accurate appraisals of the risks associated with purchasing a given asset. Instead, they often issued overly favorable ratings, due to the fact that they were paid by the same firms that were trying to sell the asset to investors. The Dodd-Frank law requires the SEC to create a ratings oversight board where investor representatives are in the majority. The board would choose a rating agency to conduct the initial evaluation of each new set of structured financial products. Before this takes place, however, the SEC is required to undertake a two-year study on the basis of which they will decide whether to implement the proposal or an alternative. (Epstein and Pollin, 2011, 8-9)

Dodd-Frank also establishes the Consumer Financial Protection Bureau (CFPB), an independent federal agency located within the Federal Reserve. The key mission of the new agency is to protect consumers from misleading and illegal practices in the credit markets. This was seen as important as it was the market for subprime mortgages which helped drive the credit bubble and triggered the financial crisis. The CFPB consolidates consumer protection services, which were previously provided by a number of different federal agencies, into one agency. The CFPB has rulemaking and enforcement authority covering a range of areas, including: checking accounts, mortgages, credit cards, and student loans. The new law also gives states the authority to go beyond CFPB rules to address local problems before they become too large. (McGhee and Gibson, 2010)

Finally, many observers have argued that the lack of regulation of the Over-the-Counter OTC derivatives markets was an important factor leading to the financial crisis. It was, after all, AIG's losing positions in the credit derivatives market which required it to be bailed out by the federal government. The Dodd-Frank Act seeks to reduce the systemic risk posed by the derivatives markets through requiring the central clearing of derivative securities, and by increasing standards on capital and liquid collateral to back derivative trades.

Corporate Governance and Executive Pay

There is ample research—Frydman and Saks (2010) for example—showing that the level of executive pay in the U.S. has grown significantly over the last 30 years or so. Moreover, as has been shown in the results presented here, there is evidence that the growth of executive pay has contributed to the growth of earnings inequality in metro areas over the 1990 to 2004 period. While explanations for the growth of executive pay in the U.S. vary, there are observers, such as Galbraith (2007) and Bebchuk and Fried (2003) and (2004), who argue that its growth is in large part due to the increasing power of executive managers within corporations to set their own pay. In other words, managers are increasingly in a position to "extract rents" from the firm. Moreover, this has occurred—it is argued—due to weaknesses in the system of corporate governance in the U.S. Proper reform of the system of corporate governance, therefore, could cause a reduction in the inflated pay of executives, and this, in turn, could reduce earnings inequality.

Interest in the American system of corporate governance—and its reform—was greatly intensified by the corporate accounting scandals in 2001-2002. Much of the interest and concern focused on the practices of the boards of directors of public companies, and their lack of independence from executive managers. Many observers believed that it was this lack of independence, moreover, which led to many of the abuses on the part of executives, including their excessive salaries. (Bebchuck and Fried, 2003, p. ix); (Elson and Gyves, 2003, p. 2) When Congress passed the Sarbanes-Oxley Act of 2002 in response to the accounting scandals, therefore, part of the Act focused on improving the independence of directors on audit committees. (Elson and Gyves, 2003, p. 12)   In addition, in 2002, the New York Stock Exchange (NYSE) issued new corporate governance listing requirements, which were subsequently adopted by NASDAQ, and AMEX, and later approved by the Securities and Exchange Commission (SEC) in 2003. These new rules similarly required companies to have boards with a majority of directors that were independent, audit and compensation committees that are comprised only of independent directors, and semi-annual executive sessions in the absence of management. (Elson and Gyves, 2003, p. 10)

Some observers have argued, however, that these new rules and the increased focus on director independence are not enough to ensure that boards are not working mostly in the interests of the executives. While the new rules do exclude some individuals from serving on the board of a particular company, there are still a large number of individuals who qualify. To really improve the independence of boards, additional incentives are needed to encourage directors to focus on the interests of shareholders. Bebchuk and Fried (2004) have suggested that the most effective way to improve board performance is to increase the power of shareholders vis-a-vis directors. One way of doing this, moreover, would be to increase shareholders' role in the appointment and reappointment of directors to the board. (p. 207)

Directions for Future Research

Regional/Local Policy

Finally, it was suggested in the introductory chapter that one of the potentially negative social effects of rising earnings inequality in metro areas is its possible association with a rising cost of living. This association might occur as new high-income residents in metro areas bid up the cost of local goods and services to levels beyond which many mid- and low-income residents can afford. Moreover, while this study offers no specific evidence in support of this view, this is potentially a very important aspect of the earnings inequality phenomenon.

A promising direction for future research in this area, therefore, would involve an examination of the relationship between the growth of earnings inequality in metro areas and the regional cost of living. One important component of the regional cost of living, moreover, is the cost of rental and owner-occupied housing. If a positive correlation between the cost of housing and earnings inequality in metros were found, this would have important implications for regional and local policy makers, specifically in the area of affordable housing policy.

APPENDIX TO CHAPTER FOUR: AD HOC IMPUTATION METHOD

As noted in Chapter four, the publicly-available earnings and employment data from the BLS' Covered Employment and Wages Program were used to calculate the measures of industrial structure. Due to the fact that these data are publicly available, there was some data suppression due to confidentiality rules.

The earnings and employment data were collected at the county level and were aggregated at the Supersector level. An example of a dataset for a given county with some data suppression appears below in Table 1. (The rows in bold are totals)   In this case, we observe that the employment and wage data for the Information and Other Services sectors are not provided. What is provided, however, is the employment and wage data for all seven of the Service Providing sectors combined, including the two missing sectors. In this case, the total is 1,517 for Employment and 19,397,739 for wages. In order to calculate Employment—and the same method is used for wages—for the Information and Other Services sectors, we take the 1,517 total and subtract the reported numbers (758+129+50+229+223), which equals 128. The employment number of 128 represents total employment for the Information and Other Services sectors combined. The question then becomes what proportion of the 128 total is accounted for

Table 1: Example of Data Suppression

Area Code	Ownership	NAICS Super Sector	Year	Employment	Wages
01079	**Total Covered**	**Total Covered**	**1990**	**7,269**	**168,034,855**
01079	Federal	Federal	1990	136	3,545,340
01079	State	State	1990	236	4,447,563
01079	Local	Local	1990	1,222	20,222,054
01079	**Private**	**Total Private**	**1990**	**5,675**	**139,819,898**
01079	**Private**	**Goods Producing**	**1990**	**4,158**	**120,422,159**
01079	Private	Natural Resources and Mining	1990	280	6,248,350
01079	Private	Construction	1990	1,605	35,728,775
01079	Private	Manufacturing	1990	2,273	78,445,034
01079	**Private**	**Service Providing**	**1990**	**1,517**	**19,397,739**
01079	Private	Trade, Transportation, and Utilities	1990	758	10,006,584
01079	Private	Information	1990	**ND**	**ND**
01079	Private	Financial Activities	1990	129	1,869,978
01079	Private	Professional and Business Services	1990	50	614,744
01079	Private	Education and Health Services	1990	229	3,440,625
01079	Private	Leisure and Hospitality	1990	223	1,521,444
01079	Private	Other Services	1990	**ND**	**ND**

by Information and what proportion by Other Services. These proportions were calculated based on the average proportions for these two sectors for all counties in the dataset combined.

APPENDIX TO CHAPTER 5: REGRESSION DIAGNOSTICS

The data used in the final regression model on page 120 were tested for outliers, nonlinearity, normality, and skewness. The regression model itself was also tested for multicollinearity and heteroskedasticity.

Outliers

The scatterplots do suggest there might be some outliers for some of the variables. Some examples include: Change Earnings Share Finance; Trade Transportation and Utilities; and Percent Change Population. When Cook's D measure is calculated for each observation, however, it is found that there are no significant outliers for any of the observations. The highest Cook's D measure is 0.23 for the Jersey City metro area. The second highest is 0.12 for the Las Vegas metro area.

Nonlinearity

Based on the scatterplots, there are no clear nonlinear relationships, so we can assume linearity.

Multicollinearity

In tables 1 and 2 below, the results of running the vif function after each regression shows that multicollinearity is not a problem in the model.

Heteroskedasticity

To test for heteroskedasticity, the predicted (fitted) values were plotted against the residuals. This scatterplot is at the bottom of the histogram and scatterplot sheet. The scatterplot shows that there does not appear to be a pattern of unequal variance of the error term. Heteroskedasticity is, therefore, not a problem for the model.

Normality and Skewness

In terms of assessing normality and skewness of the variables, based just on the histograms of each variable, its pretty obvious that the following variables are not normally distributed: avgpropblack, avgprophispanic, chngprophisp, and avgpropdoctor. These variables were not, however, transformed.

Table 1: Regression Output from Stata

Source	SS	df	MS
Model	7.25465656	16	.453416035
Residual	6.53299765	238	.02744957
Total	13.7876542	254	.054282103

Number of obs	=	255
F(16, 238)	=	16.52
Prob > F	=	0.0000
R-squared	=	0.5262
Adj R-squared	=	0.4943
Root MSE	=	.16568

Perc Change Theil 90to04	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Change WS Construction	-1.635051	.9753005	-1.68	0.095	-3.556375	.286273
Change WS Educ & Health	-.8992967	.595283	-1.51	0.132	-2.071993	.2733998
Change WS Finance	3.759717	.5141151	7.31	0.000	2.74692	4.772515
Change WS Info	-.0035549	.9041755	-0.00	0.997	-1.784764	1.777654
Change WS Prof & Bus	1.426747	.4518424	3.16	0.002	.5366258	2.316868
Change WS Trade,Transp	-.8589382	.4859436	-1.77	0.078	-1.816238	.0983616
Perc Change Population	-.2036765	.0847007	-2.40	0.017	-.3705352	-.0368177
Avg Share Black	.3994955	.1152583	3.47	0.001	.1724388	.6265522
Avg Share Hisp	.2877997	.0986543	2.92	0.004	.0934525	.4821468
Change Share Black	-1.878168	.9006495	-2.09	0.038	-3.652431	-.1039054
Change Share Hisp	.5493274	.4404545	1.25	0.214	-.3183598	1.417015
Avg Share Bachelors	1.59113	.4757264	3.34	0.001	.6539576	2.528302
Avg Share Doctorate	-5.632124	1.628317	-3.46	0.001	-8.839879	-2.424369
Change Share Bachelor	-.7173015	1.414053	-0.51	0.612	-3.50296	2.068357
Change Share Masters	4.899295	2.246905	2.18	0.030	.4729337	9.325656
Change Share Doctorate	16.3493	6.622015	2.47	0.014	3.304054	29.39455
Constant	-.1910164	.0629899	-3.03	0.003	-.3151054	-.0669274

Table 2: VIF function output.

. vif

Variable	VIF	1/VIF
Avg Share Bachelors	3.68	0.271715
Avg Share Doctorate	2.15	0.464191
Change Share Bachelor	2.64	0.378726
Change Share Masters	2.49	0.402235
Change Share Doctorate	1.52	0.657170
Avg Share Hispanic	2.09	0.479130
Avg Share Black	1.52	0.658961
Change Share Black	1.47	0.681380
Change Share Hispanic	2.29	0.437407
Percent Change Populat	1.77	0.566457
Change WS Prof & Bus	1.39	0.720087
Change WS Educ & Health	1.39	0.721563
Change WS Finance	1.33	0.753121
Change WS Construction	1.30	0.770610
Change WS Info	1.15	0.868905
Change WS Trade,Transp	1.15	0.870685
Mean VIF	1.83	

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James Lawrence grew up in the quaint town of Bethel, CT. He received his Bachelor of Arts in International Affairs at the George Washington University in Spring,1993. He would later receive his Master of Public Affairs from the LBJ School at the University of Texas at Austin in the Fall, 2001. James received his Doctorate in Public Policy from George Mason University in the Fall of 2013. Jim currently works as a Survey Statistician at the US Census Bureau.