Breaking Down Increasing Earnings Inequality in the U.S. 1990-2004

Jessica Sprinkel
Dr. Allin Cottrell
Dr. Donald Frey
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Abstract

In this paper, I investigate the causes of increasing earnings inequality in the U.S. between 1990 and 2004. I calculate Gini coefficients of individual earnings for specific groups of the workforce (determined by such characteristics as industry and occupation classification, sex, race, education level, age, and coverage by a labor union contract) for each year. I then break down the total change in earnings inequality between the two years into between-group inequality (due to changing shares of subgroups) and within-group inequality (due to changing inequality within each subgroup). I find that the increase in total inequality during this time period was primarily due to an increase in within-group inequality, and that in some cases, between-group inequality actually decreased. In light of these findings, I evaluate several of the prevailing theories to explain the presence of increasing income inequality in the U.S. Finally, I investigate the credibility of the popular "vanishing middle market" theory by determining certain characteristics of the middle class (which I define as a function of the real poverty level) and find that this middle group has only slightly decreased in size, if not remained unchanged.

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Introduction

Increasing income inequality has been well-documented in the economic literature for the past 30 years, and many authors have explored the effects of this phenomenon, including increasing consumption and wealth inequality, an alleged "disappearance of the middle class," and a decreasing effective demand. Far fewer authors, however, have looked into the causes of this increasingly alarming trend. One clear exception is McNeil (1998), who analyzed household income inequality in the U.S. between 1969 and 1996. This time period includes the early 1980s, during which income inequality increased sharply, a change usually attributed to a changing industrial structure, including the shipping out of many manufacturing jobs during the 1970s. In this paper, I propose to update the work of McNeil, as well as prove that the growth and shrinkage of different industries or occupations did not significantly contribute to an increase in earnings inequality between 1990 and 2004, and in fact, that this restructuring actually worked to decrease total inequality in some cases.

In my analysis, I define several groups of the working population by such characteristics as industry, occupation, sex, race, education level, labor union contract coverage, and age. I then break down the total change in inequality for each of these groups into between-group change (or the change in inequality due to the growth and shrinkage of different groups) and within-group change (or the change in inequality for each group assuming the same share of the total). I find that within-group changes in inequality are overwhelmingly the main contributors of the increase in total earnings inequality, and thus, that the restructuring of the workforce by industry and occupation are of little use in explaining the increase in total earnings inequality. I find more promising results for groups based on education level and labor union contract coverage, which are discussed in later sections. Finally, I try to get a notion of the middle class by defining the lower and upper bounds as multiples of the individual poverty level. I find that the middle class shrank only slightly between 1990 and 2004, which casts doubt on the "vanishing middle class" argument prevalent in the popular media.

Literature Review

Trends in Income Inequality

Kruegger and Perri (2006) explain that the sharp increase in earnings and income inequality for the U.S. in the last 25 years is a well-documented fact, and that many authors have found that this trend is attributable both to increases in the dispersion of the permanent component of income and to an increase in the volatility of the transitory component of income (163). Kruegger and Perri use data from the Consumer Expenditure survey to demonstrate that the recent increase in income inequality in the U.S. has not been accompanied by a corresponding rise in consumption inequality. They argue that much of this divergence is due to different trends in within-group inequality, which has increased significantly for income, but little for consumption (163). Kruegger and Perri analyze cross-sectional income and consumption data between 1980 and 2003 and find that despite the surge in income inequality, consumption inequality has increased only moderately.[1] Moreover, they find that income inequality has increased substantially, both between and within groups of households with the same characteristics (such as education, sex, and race). Even though between-group consumption inequality has

[1] Johnson, however, finds that consumption inequality increases almost as much as income inequality, suggesting instead that the increase in income inequality is due mainly to changes in permanent and not transitory income if consumption is a good measure of permanent income (174).

tracked between-group income inequality quite closely, however, within-group consumption inequality has increased much less than within-group income inequality.

Their hypothesis is that an increase in the volatility of idiosyncratic labor income (which they identify as the increase in within-group inequality) has not only been an important factor in the increase in income inequality, but has also caused a change in the development of financial markets, allowing individual households to better insure against these (now bigger) idiosyncratic income fluctuations. They conclude that an increase in the volatility of income—keeping the persistence of the income process constant—always leads to a smaller increase in consumption inequality within the group that shares income risk. The model they create illustrates the idea that the structure of the credit markets in an economy is endogenous and may evolve in response to higher income volatility (164).[2]

McNeil (1998) actually finds that while per capita income rose 51% between 1969 and 1996, the real median household income rose by only 6.3%. McNeil argues that the stagnation of median household income between 1969 and 1996 may, in fact, largely be a reflection of changes in the size and composition of households rather than a reflection of a stagnating economy (1). Burtless (2007), too, is skeptical of how much inequality has actually increased. He admits that there was a rapid increase during the 1980s, which perhaps has even been understated in the current economic literature, but contends that income inequality remained relatively constant, and in some instances declined, after 1989.

[2] This relationship between income and consumption inequality is also documented by other authors, including Attanasio et al. (2002), who demonstrate that income variance has increased at a faster rate than expenditure variance, supporting the notion that a higher volatility in the transitory component of income is the main source of increasing inequality.

Possible Explanations

There have been many explanations put forth in the literature, which of course differ depending on the income inequality trends found by each researcher. On the theoretical side, Pikkety and Saez (2003) reference Kuznets's hypothesis, which states that income inequality should follow an inverse-U shape along the development process, first rising with industrialization and then declining, as more and more workers join the high-productivity sectors of the economy (Kuznets 1955). They argue that the Kuznets curve today is widely assumed to have doubled back on itself, especially in the United States, with a period of falling inequality observed during the first half of the twentieth century being succeeded by a very sharp reversal of the trend since the 1970s (1-2). Instead of tossing aside the Kuznets curve in their analysis of income inequality, however, they instead contend that since the 1970s a new industrial revolution has taken place. Thus, the past 30 years would have just been a remake of the previous inverse-U curve. This would explain the increasing inequality over the time period, and would support the hypothesis that inequality will decline again at some point in the future, as more and more workers benefit from innovations (2).

Pikketty and Saez (2003) argue that both the downturn and the upturn of top wage shares, however, seem too sudden to be accounted for by technical change alone. Instead, they suggest that other factors, such as changes in labor market institutions, fiscal policy, or more generally, social norms regarding pay inequality may have played important roles in the determination of the wage structure. They note other studies that analyzed the effects of the Tax Reform Act of 1986 (TRA86), which emphasized that a large part of the response observable in tax returns was due to income shifting between the corporate sector and the individual sector.[3] They do not deny that fiscal manipulation can have substantial short-run effects, but argue that most long-run inequality trends are the consequence of real economic change, and thus, a short-run perspective might lead to attribute improperly some of these trends to fiscal manipulation (3-4).

Kruegger and Perri (2006) argue that between-group inequality is largely attributable to fixed and observable characteristics of the household (e.g. education, experience, and sex). Although between-group inequality changes over time (returns to these characteristics can change over time, as in the case of the increase in the college premium), it is unlikely that households can insure against these changes. Therefore, increases in between-group inequality should translate into similar increases in between-group consumption inequality. On the other hand, within-group income inequality is a residual measure that includes inequality caused by idiosyncratic income shocks. Therefore, according to Kruegger and Perri, increases in within-group income inequality are at least partly attributable to an increase in the volatility of idiosyncratic income shocks. Their main focus is how well households can insulate their consumption from an increase in the volatility of these idiosyncratic income shocks. They argue that the better households can insure against these shocks, the less we can expect within-group consumption inequality to increase in response to an increase in within-group income inequality. They regress income and consumption on several characteristics[4] and find that they explain about 25% of the cross-sectional variation of income and consumption in 1980 (169). Lastly, they illustrate how the extent of risk sharing depends on how abundant capital income is for each household (see 174-175).

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[3] See Slemrod (1996), Gordon and Slemrod (2000).

[4] These characteristics include sex, race, years of education, experience, interaction terms between experience and education, dummies for managerial/professional occupation, and region of residence.

McNeil (1998) finds two factors that influence income inequality in the United States: changes in the employment status of household members, and changes in the educational attainment levels of household members. He states that in 1996, the average number of year-round full-time workers in two-or-more-person households with incomes above the median was 1.4, up 14% from the 1969 level. The comparable figure for two-or-more-person households with incomes at or below the median was 0.5, unchanged from the 1969 level. The data also show a sharp increase in the educational attainment levels of individuals regardless of the income position of the household. From 1969 to 1996 in households with incomes above the median, the proportion of individuals 25 years old and over with a college degree grew from 16% to 33%. Over the same time period in households with incomes below the median, the proportion of individuals 25 years old and over with a college degree grew from 5% to 11%.

McNeil (1998) argues that the fact that the average income of households at or below the median was essentially stagnant at the same time that the educational attainment levels of people in these households rose sharply presents something of a puzzle, though he warns that such comparisons oftentimes can be misleading if the characteristics of the reference unit change substantially. He then shows that in fact there have been important changes over time within household types. He notes that one change has been the increased labor force participation of women: from 1969 to 1996, the proportion of wives working year-round full-time rose from 17% to 39% for married couples with children, from 42% to 60% for married couples with no children and a householder less than 40 years old, and from 31% to 46% for married couples with no children and a householder between the ages of 40 and 64 years (2).

Weinberg (1996) also emphasizes the changes that have occurred within the nation's labor market and its household composition. He demonstrates that the wage distribution has become considerably more unequal with more highly skilled, trained, and educated workers at the top experiencing real wage gains and those at the bottom real wage losses. He argues that one factor is the shift in employment from those goods-producing industries that have disproportionately provided high-wage opportunities for low-skilled workers, towards services that disproportionately employ college graduates, and towards low-wage sectors such as retail trade. He admits, however, that within-industry shifts in labor demand away from less-educated workers are perhaps a more important explanation of eroding wages than the shift out of manufacturing (3-4).

Weinberg (1996) also cites intensifying global competition and immigration, the decline of the proportion of workers belonging to unions, the decline in the real value of the minimum wage, the increasing need for computer skills, and the increasing use of temporary workers as causes of income inequality. He argues that long-run changes in living arrangements have taken place that have tended to exacerbate the differences in household incomes. For example, divorces and separations, births out of wedlock, and the increasing age at one's first marriage have led to a shift away from married-couple households and toward single-parent and non-family households which typically have lower incomes. In addition, the increasing tendency over the period for men with higher-than-average earnings to marry women with higher-than-average earnings has contributed to widening the gap between high-income and low-income households (4).

Johnson and Shipp (1999) find that the trends in the distribution of income and consumption and the response of these trends to changes in inflation and unemployment were similar before 1980. They find that unemployment does not significantly affect the inequality measures and that inflation has a progressive effect (i.e. that a decrease in inflation is associated with an increase in inequality). Finally, they find that the relationship between inequality and macroeconomic variables during the 1990s may be similar to the relationship that existed prior to 1980. They note that many studies, contrary to their findings, have demonstrated that increasing unemployment was associated with increasing income inequality, that inflation was associated with decreasing income inequality, and that unemployment had a more significant impact on income inequality than did inflation; the relationship between the level of income inequality and macroeconomic growth appeared to be fairly stable. Many studies have also found that during the 1980s such relationships ceased to exist, however—i.e., that a growing economy was not necessarily associated with improving the economic well-being of the lower-income groups (173-174).[5]

To examine the effect of the business cycle on inequality, Johnson and Shipp (1999) examine three macroeconomic variables—inflation, unemployment, and real per-capita transfers. They note that even though other studies use real GDP to model the business cycle, they chose to use unemployment because unemployment is highly correlated with GDP and, more importantly, because income and consumption decisions may be more sensitive to unemployment than to GDP. They find that the decrease in inflation during the 1980s was associated with an increase in income inequality. Because inflation tends to benefit debtors at the expense of creditors, the fall in inflation during the 1980s could have benefited asset holders, who tend to have higher incomes. Alternatively, because people in the lower-income groups are more likely to receive

[5] See Blank and Card (1993); Cutler and Katz (1991); and Ruggles and Stone (1992).

transfers, inflation is detrimental to these groups if transfers do not rise as quickly as average wages (175-176).

Johnson and Shipp (1999) also find that although unemployment fell from 1982 to 1988, income inequality continued to increase, suggesting that generally improving macroeconomic conditions do not necessarily decrease inequality. Unemployment tends to occur more often in low-income households (who may also be liquidity constrained), permanently reducing their income and consumption, resulting in an increase in inequality. They argue that the high unemployment rates of the early 1980s may have had an impact on inequality that did not taper off until the early 1990s. Other researchers such as Medoff (1994) and Perry and Schyltze (1993) show that the 1980s were different than any other time period because unemployment was more permanent in nature—i.e., the share of unemployment that was due to permanent job loss was greater during the 1980s than it was before 1980. Therefore, transfers may have a mitigating effect on inequality. From 1980 to 1987, per-capita real transfers rose more slowly than from 1987-1994, which corresponds to the trend in consumption inequality, which increased steadily until 1987 and then remained fairly constant. Their regression results suggest that income and consumption inequality react similarly to macroeconomic conditions, and that inflation is the most significant factor for both income and consumption inequality. They conclude that since the 1980s, unemployment has not significantly affected the inequality measures, and that transfers have a significant progressive effect—i.e., that an increase in transfers decreases inequality (177).

Lemieux (2006) finds that residual wage inequality only accounts for a small share of the overall growth in wage inequality. Furthermore, all of the growth in residual wage inequality occurs during the 1980s. He argues that if the increase in the price of unobserved skills was the most important source of growing wage inequality (as opposed to education and experience), he should have seen a large increase in the return to various measures of "ability" and in the male-female, or black-white, wage gap (to the extent that part of these gaps are due to differences in unobserved skills). He argues that the fact that none of those wage differentials expanded over the last three decades is a major challenge to the view that the return to unobserved skills grew a lot during this period. He demonstrates that the timing of changes in residual wage inequality closely matches the timing of changes in the college-high school wage premium, and that both measures grew in the 1980s but declined or remained stable during the 1970s and 1990s (3). Overall, Lemieux finds that the magnitude and timing of the growth residual wage inequality provides little evidence of a pervasive increase in the demand for skill due, for instance, to skill-biased technological change.

Jenkins and Van Kerm (2006) take a different approach than the majority of researchers in his analysis of the relative income positions of individuals. They provide an analytical framework within which changes in income inequality over time are related to the pattern of income growth across the income range and the reshuffling of individuals in the income pecking order. They find that over the 1980s, there was a substantial reshuffling of positions in the U.S. income distribution, which they argue many inequality studies fail to take into consideration. As they illustrate, the person with a family income at the 20th percentile in 1981 was unlikely to be the person at the 20th percentile in 1986. They show that the poor *did* gain ground and move ahead in the distribution during the 1980s—i.e. the income inequality was pro-poor—even though the rich far outpaced them in terms of income growth—i.e. the poor still fared badly in relation to the rich (542).

Definitions of Income

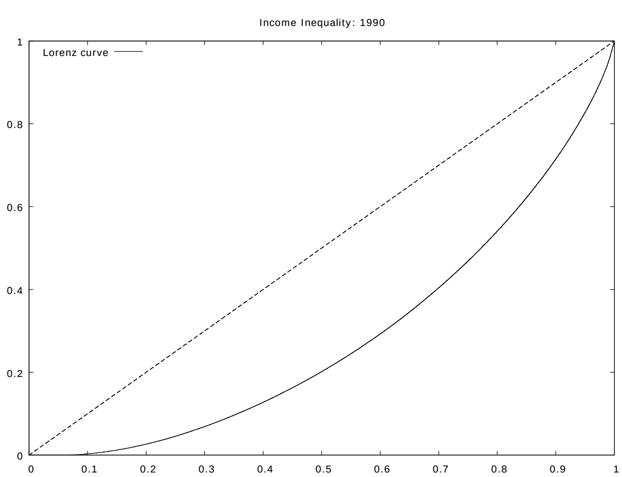
It is important to note that estimates of income inequality can vary greatly depending on what definition of income is used. Five popular definitions of income that researchers have used are summarized in the table below. First, *money income* (MI) includes earnings, unemployment compensation, workers' compensation, Social Security, Supplemental Security income, public assistance, veterans' payments, survivor benefits, pension or retirement income, interest, dividends, rents, royalties, income from estates and trusts, educational assistance, alimony, child support, cash assistance from outside the household, and other miscellaneous sources it is income before deductions for taxes or other expenses and does not include lump-sum payments or capital gains.

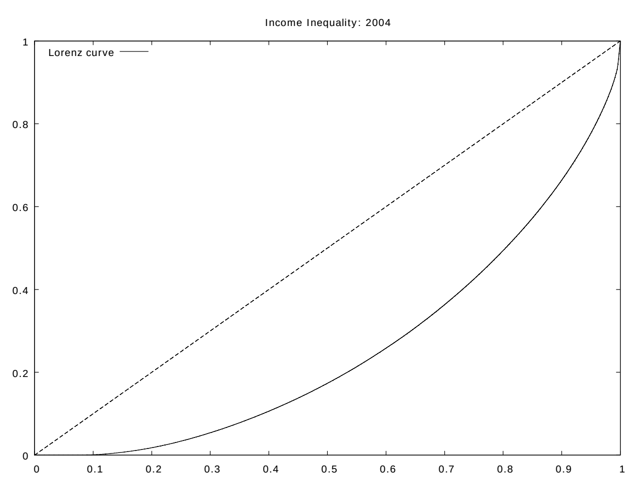
Other income definitions	Money Income (**MI**) + realized capital gains/losses - federal and state income taxes - payroll taxes → **MI-Tx** + employer-provided health benefits + noncash transfers except for Medicare and Medicaid → **MI-Tx+NC-MM** + Medicare and Medicaid benefits → **MI-Tx+NC** + annual benefits of converting one's home equity into an annuity, net of property taxes → **MI-Tx+NC+HE**

Weinberg (1996) demonstrates in his article that the distribution of incomes is more equal under a broadened definition of income that takes account of the effects of taxes and noncash benefits. In addition, he shows that government transfer benefits play a much more equalizing role on income than do taxes (3). It is important to note that if the income definition does not include government taxes and transfers, such as the one used by Kruegger and Perri and the one used in my analysis, changes in government income redistribution policies cannot be responsible for the divergence between two series such as income and consumption inequality.

Measures of Income Inequality

There are also different measures of inequality one can use. The most frequently used measure is the Gini coefficient[6], which is defined as a ratio of the areas on the Lorenz curve diagram. It ranges from 0, where every family (household) has the same income, to 1, where one family (household) has all the income (1). When the Gini coefficient is small, the Lorenz curve is narrow; when the coefficient is large, the Lorenz curve is wide. This measure is used by Johnson and Shipp (1999), who also use ordinary least squares to estimate an equation for the impact of macroeconomic variables on inequality (176). Below are the Lorenz curves for 1990 and 2004 income inequality.





[6] The Gini coefficient is calculated by the following equation: $G = 1 - 2\int_0^1 L(X)dX$

Jenkins and Van Kerm (2006) assert that when income inequality is measured using any member of the generalized Gini class of indices, the change in inequality between two points in time can be additively decomposed into two components, one summarizing mobility in the form of reranking, and one summarizing progressivity in income growth—i.e. whether income growth is pro-poor rather than pro-rich. They argue that the key to resolving the paradox of pro-poor growth in which the poor still fared badly in relation to the rich is the recognition that membership of income groups such as the poor and the rich changes over time. They suggest that an analysis of income distribution trends using cross-sectional data sets ignores the reshuffling of individuals in the income distribution over time, whereas this mobility is an integral part of dissecting the changes to income inequality over time. More recently, Ravallion and Chen (2003) have developed a measure of pro-poor income growth that is directly related to changes in the Watts poverty index.[7] Xu and Osberg (2002) show that the proportionate change in the Sen-Shorrocks-Thon poverty index[8] is related to proportionate changes in the proportion poor, growth in mean income among the poor, and changes in inequality of poverty gap. However, it is the fortunes of income groups—the poor in particular—that are tracked, not the fortunes of individuals, as in their approach (532-533).

Kruegger and Perri (2006) actually portray the trend of income inequality using four common measures (computed using CE population weights). They demonstrate that

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[7] The Watts poverty is calculated by the following equation: $W = \frac{1}{N}\sum_{i=1}^{q}[\ln(z - \ln(y_i)$

where the N individuals in the population are indexed in ascending order of income (or expenditure), and the sum is taken over the q individuals whose income (or expenditure) y_i falls below the poverty line z.

[8] This index is calculated by the following equation: I = (rate)*(gap)*(1+G(x))

where *rate* is the percentage of the population with incomes below the poverty line (sometimes called the head count ratio), *gap* is the average percentage gap between the incomes of the poor and the poverty line and *G(x)* is the Gini index of inequality of the poverty gap among all people.

during 1980-2003, the Gini index increased from 0.3 to around 0.37, and that the variance of the logs displayed an increase of more than 20%. The 90/10 ratio for income surged from 4.2 to over 6, suggesting a large divergence between the two tails of the income distribution over time, and the 50/10 ratio displayed an increase from 2.2 to 2.7, revealing that households in the bottom tail of the income distribution have lost ground relative to the median (166). On the other hand, Attanasio et al. measure inequality by calculating the variance of the logs. They look at variances of earnings shocks in relation to consumption changes. They are not looking at total income distribution, but rather within-group income inequality (C53).

Brown (2004), who analyzes income distribution in terms of the level of poverty that exists, uses the well-known Theil Index.[9] He calculates the index for each quintile, as well as for the whole group (297). Brown admits that attempting to specify an expenditure level equivalent to a socially necessary minimum within the context of contemporary U.S. society unavoidably entails some degree of arbitrariness. One might argue that the Social Security Administration (SSA) official poverty line furnishes a reasonable measure of the socially necessary minimum. But the SSA poverty index is an absolute standard—i.e., it makes no adjustments for a general increase in living standards. As Veblen (1899) and others have observed, people's feelings about the satisfactoriness of their own material living standards are influenced by the consumption habits displayed

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[9] The Theil index is calculated by the following equation: $T = \frac{1}{N}\sum_{i=1}^{N}(\frac{x_i}{\bar{x}} \cdot \ln\frac{x_i}{\bar{x}})$

where x_i is the income of the *i*th person, $\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$ is the mean income, and *N* is the number of people. The first term inside the sum can be considered the individual's share of aggregate income, and the second term is that person's income relative to the mean. If everyone has the same (i.e. the mean) income, then the index=0. If one person has all the income, then the index = ln*N*.

by others. From this viewpoint, a poverty threshold should be relative in the sense of positioning the individual in unchanging (economic) proximity to the typical individual. Moreover, the most widely used relative poverty definition in cross-national studies is 50% of median household income, adjusted for differences in household size. This relative poverty definition is taken as the best available proxy for the socially necessary minimum level of income (296).

Available Data

As Li and Zou (1998) write, "empirical studies in income distribution are often limited by the available data" (322). Much of the current research focuses on the relationship between income and consumption inequality, and therefore uses datasets such as the Consumer Expenditure Survey and the Current Population Survey, both administered by the U.S. Census Bureau. While these surveys have their strengths, one problem with all Census data is that the standard measure of income "excludes in-kind benefits and capital gains, and ignores the effects of income and payroll taxes. The Bureau recognizes these problems, and it publishes several alternative measures of inequality which use different definitions of income," which yield less substantial increases in income inequality, especially during the 1990s (Burtless 4). The Census Bureau questionnaire also does not provide accurate or consistent assessments of the incomes of the top 2.0-2.5% of income recipients. This is because (1) the respondents' answers are top-coded for privacy purposes, and (2) the sample of high-income recipients is too small to give an accurate or consistent estimate of the incomes of the very top income recipients, say, those with incomes above $750,000 a year" (4). Thus, some researchers have chosen to use individual tax returns data, which perhaps yield a better estimation of income for the rich, but are more cumbersome to work with.

Present Analysis

In my study of earnings inequality, I consult data from the Survey of Income and Program Participation, published by the Census, for the years 1990 and 2004. I chose this dataset because it gives quite detailed data on income, gender, labor union participation, children, education and other variables in terms of individuals, families and households. I also choose to use Gini coefficients to measure inequality, primarily because they are the most widely used measure in the current literature, making it easy to benchmark my findings against others already calculated. In addition, Gini coefficients are a bit simpler to understand when trying to get a handle on the entire income distribution, as opposed to other measures such as the 90/10 ratio and the 50/10 ratio, which place more emphasis on a particular segment of the distribution. I do not carry out any regressions; rather, I treat the Gini coefficients similar to price indexes as I break down total earnings inequality into within- and between-group inequality. I break down the workforce by several characteristics, including industry, occupation, gender, race, education level, labor union participation, and age. Because I deal with real earnings and do not include any real capital gains or government transfers, the effects of fiscal policy and changing patterns of inflation and unemployment are zeroed out, even though they likely do play some role in determining the direction and severity of income inequality. I wanted to focus on the effects of changing characteristics of workers in the level and growth of their real earnings, however, and thus, I chose to eliminate these effects. Finally, in my evaluation of the “vanishing middle class” theory, I use the real individual poverty level published by the Census, to define this middle group whose size and characteristics I measure for both 1990 and 2004.

An Explanation of the Tables

Industrial Breakdown

In Table 1a, I calculate the mean, the coefficient of variation (the standard deviation/mean), and the Gini coefficient for individual earnings, as well as the percentage each industry constitutes of the total workforce in 1990 and 2004. The mean and coefficient of variation have been adjusted to reflect 2004 dollars, and I have noted the percent change for each variable. At the aggregate level, the mean of real earnings increased 14.3%, and all industries showed an increase in the mean except for Agriculture, Forestry and Fisheries, Entertainment and Recreation Services, and Professional Services. The highest increase in the mean was in the Business and Repair Services industry, which grew 56.6%. The coefficient of variation also increased across the board (43.1% at the aggregate level). The industry that had the highest increase was Professional Services, whose coefficient grew 76.8%. The only industry whose coefficient of variation decreased was Wholesale Trade-nondurable goods (-2.1%).

At the aggregate level, the Gini coefficient increased from 0.43 to 0.49, and all of the industries showed increases in the Gini coefficient except for Wholesale Trade-nondurable goods, which showed a small decrease from 0.43 to 0.41. Agriculture, Forestry and Fisheries had a high Gini coefficient in both years (0.53 in 1990 and 0.66 in 2004), though some of that inequality can probably be attributed to the inclusion of capital gains as a part of earnings. Entertainment and Recreation Services also had a high Gini coefficient in both years (0.51 in 1990 and 0.52 in 2004), and Professional Services

Table 1a: Industry

	Mean			Coefficient of Variation			Gini Coefficient	
Industry	1990	2004	% change	1990	2004	% change	1990	2004
Agriculture, Forestry, and Fisheries	1329.7	1186.3	-10.8%	1.2	2.0	58.2%	0.53	0.66
Mining	3768.8	4329.7	14.9%	0.6	1.0	69.1%	0.32	0.40
Construction	2379.1	2558.6	7.5%	0.7	1.0	27.5%	0.39	0.44
Manufacturing-nondurable goods	2731.3	3131.2	14.6%	0.8	1.0	34.1%	0.40	0.43
Manufacturing-durable goods	3164.6	3591.1	13.5%	0.7	1.0	39.5%	0.35	0.40
Transportation	2963.2	3042.1	2.7%	0.6	0.9	51.3%	0.33	0.42
Communications	3401.4	3457.3	1.6%	0.6	1.0	65.1%	0.34	0.44
Utilities and Sanitary Services	3321.5	4411.1	32.8%	0.5	0.8	52.1%	0.30	0.35
Wholesale Trade-durable goods	2841.5	3371.8	18.7%	0.8	1.0	30.4%	0.39	0.41
Wholesale Trade-nondurable goods	2683.8	3006.3	12.0%	0.9	0.8	-2.1%	0.43	0.41
Retail Trade	1416.8	1949.5	37.6%	1.0	1.3	32.1%	0.49	0.51
Finance, Insurance, and Real Estate	2846.8	3886.7	36.5%	0.8	1.3	54.1%	0.42	0.49
Business and Repair Services	2080.3	3257.9	56.6%	1.0	1.3	33.6%	0.48	0.52
Personal Services	1270.6	1598.3	25.8%	1.1	1.1	4.5%	0.47	0.51
Entertainment and Recreation Services	1718.4	1230.2	-28.4%	1.0	1.2	17.6%	0.51	0.52
Healthcare	2316.9	2835.3	22.4%	0.8	1.4	72.0%	0.39	0.47
Education	2489.6	2658.9	6.8%	0.8	1.0	27.2%	0.41	0.43
Professional Services	2518.7	1985.0	-21.2%	0.9	1.6	76.8%	0.46	0.54
Public Administration	3412.3	3544.8	3.9%	0.6	0.8	30.4%	0.33	0.36
Armed Forces	2931.6	4004.5	36.6%	0.5	0.9	63.9%	0.30	0.36
Aggregate	2415.2	2760.4	14.3%	0.8	1.2	43.1%	**0.43**	**0.49**

	% of total employed		
Industry	1990	2004	%-point change
Agriculture, Forestry, and Fisheries	1.6%	1.3%	-0.3%
Mining	0.6%	0.4%	-0.2%
Construction	5.0%	6.2%	1.2%
Manufacturing-nondurable goods	7.1%	4.7%	-2.4%
Manufacturing-durable goods	11.4%	8.1%	-3.3%
Transportation	4.6%	2.7%	-2.0%
Communications	1.4%	3.8%	2.4%
Utilities and Sanitary Services	1.4%	0.8%	-0.5%
Wholesale Trade-durable goods	2.1%	0.2%	-1.9%
Wholesale Trade-nondurable goods	1.9%	1.7%	-0.2%
Retail Trade	17.0%	11.8%	-5.2%
Finance, Insurance, and Real Estate	6.4%	5.8%	-0.6%
Business and Repair Services	5.6%	9.3%	3.7%
Personal Services	3.3%	2.8%	-0.5%
Entertainment and Recreation Services	1.2%	8.6%	7.4%
Healthcare	8.9%	11.4%	2.6%
Education	8.7%	9.5%	0.8%
Professional Services	5.2%	3.4%	-1.8%
Public Administration	5.3%	5.9%	0.7%
Armed Forces	1.0%	1.0%	-0.1%
Aggregate	99.7%	99.4%	---

had a big jump from 0.46 in 1990 to 0.54 in 2004. I also calculated the percentage that each of the industries made up of the workforce for both years. The overall change was asymmetrical, as most industries shrank slightly, and a few grew by more substantial amounts. Retail Trade showed the biggest decrease of 5.2% while Entertainment and Recreation Services, on the other hand, saw a huge increase of 7.4% (the next largest increase was Healthcare at 2.6%).

In the first column of Table 1b, I multiply the Gini coefficient of each industry by the percentage of the workforce it constitutes, and then add these together to get the aggregate Gini coefficient for each year. This exercise is essentially checking that the aggregate Gini coefficient has an additive property, so the goal is to get as close as possible to the 0.43 and 0.49 coefficients I calculated on the previous table. The Gini coefficients in Table 1b, which are weighted by employment, *are* slightly lower than the ones I calculated in Table 1a, which are in effect weighted by income (the standard notion of the Gini coefficient): 0.4190 compared with 0.43, and 0.4691 compared with 0.49. We can say, then, that when the Gini coefficient is weighted by employment, more weight is put on industries whose earnings are more equal, and actually, the effect is even more pronounced in 2004, where the ratio between the employment-weighted and the income-weighted coefficients is smaller than it was in 1990. We can see this in the previous table in the highly unequal industries whose mean real income decreased from 1990 to 2004 that contributed significantly to the Gini coefficient in Table 1a, but because they constituted only a small percentage of the total workforce, they did not contribute much to the coefficients in Table 1b.

Table 1b: Industry Breakdowns							
			Over time			Aggregate Gini Coefficient assuming no within-industry inequality	
With own year weights			With opposite weights, base year 1990			Using a simulated population of 1000	
1990	2004		Shares change	Inequality changes		1990	2004
0.0084	0.0088		0.0070	0.0105		0	0
0.0018	0.0015		0.0012	0.0023		0	0
0.0196	0.0273		0.0242	0.0221		0	0
0.0286	0.0203		0.0189	0.0307		0	0
0.0398	0.0324		0.0284	0.0455		0	0
0.0153	0.0112		0.0088	0.0195		0	0
0.0047	0.0167		0.0129	0.0061		0	0
0.0041	0.0029		0.0025	0.0047		0	0
0.0081	0.0007		0.0007	0.0085		0	0
0.0081	0.0068		0.0071	0.0078		0	0
0.0832	0.0602		0.0579	0.0865		0	0
0.0268	0.0284		0.0244	0.0313		0	0
0.0270	0.0484		0.0447	0.0293		0	0
0.0155	0.0143		0.0132	0.0168		0	0
0.0063	0.0448		0.0440	0.0065		0	0
0.0345	0.0537		0.0445	0.0416		0	0
0.0359	0.0410		0.0391	0.0376		0	0
0.0240	0.0185		0.0157	0.0281		0	0
0.0173	0.0213		0.0195	0.0189		0	0
0.0100	0.0100		0.0100	0.0100		0	0
0.4190	**0.4691**		**0.4245**	**0.4643**		**0.15**	**0.16**
Two calculations for within-industry inequality growth:							
Total change - between-industry change = within-industry change					*0.0446*	90.2%	
Total change - within-industry change = between-industry change					0.0049	9.8%	
Weighted within-industry change					*0.0453*	89.1%	
Weighted between-industry change					0.0055	10.9%	

In the second column, I break down the change in total inequality into the change in within- and between-industry inequality. I define the change in between-industry inequality as the change in the Gini coefficient due to certain industries growing or shrinking. Thus, I multiply the 1990 Gini coefficient by the 2004 share of the workforce for each industry, and then add together all the shares of the Gini coefficient to get the aggregate Gini coefficient. I define the change in within-industry inequality as the change in the Gini coefficient due to changes in inequality assuming that no industries grow or shrink. Thus, I multiply the 2004 Gini coefficient by the 1990 share of the workforce for each industry, and then add together all the shares of the Gini coefficient to get the aggregate Gini coefficient.

I then show two different ways to calculate within-industry inequality. The first calculation takes the total change in inequality (0.4691-0.4190) and subtracts the between-industry change (0.4245-0.4190) to get the within-industry change in inequality. I then subtract the within-industry change in inequality (0.4632-0.4190) from the total change in inequality (0.4691-0.4190) to get the between-industry change in inequality. In the second method, I simply take the weighted calculation I used in the first method (0.4245-0.4190 to get the between-industry change in inequality, and 0.4643-0.4190 to get the within-industry change in inequality). I find by using both methods that while the change in between-industry inequality contributes a slight amount to the increase in total earnings inequality, most of the increase in total inequality is attributable to an increase in within-industry inequality. In other words, the change in earnings inequality was more of an “overall” effect, and that it was not, at least significantly, due to a changing industrial structure.

This conclusion is confirmed by my calculations in the third column. Here I create a simulated population of 1000 in which all the workers of each industry earn the mean for that industry (i.e. for 1990, 16 people earn $1329.7, six people earn $3768.8, 50 people earn $2379.1, etc.) in order to assume no within-industry inequality. As opposed to the second column which calculates the change in inequality over time, the third column calculates the actual between-industry inequality for each year. In other words, 0.15 represents the amount of inequality that would exist if within-industry inequality were zero in 1990, and 0.16 represents the amount of inequality that would exist if within-industry inequality were zero in 2004. From these results it is clear that the contribution of between-industry inequality is small when compared with that of within-industry inequality on total inequality for both years because the ratios of 0.15 to 0.43, and 0.16 to 0.49 are quite small; the majority of total inequality is left unexplained.

Occupational Breakdown

Because slicing the workforce by industry does not seem to explain the bulk of the total change in inequality, I repeat the thought experiment for occupation in Tables 2a and 2b. In Table 2a, I again calculate the mean, coefficient of variation and Gini coefficient for earnings, as well as the percentage of the workforce each occupation constitutes. At the aggregate level, the mean of earnings increased 14.3%, and all occupations showed a moderate increase except for Technicians and Related Support, Farming, Forestry and Fishing, and Precision Production, Craft and Repair. The real earnings of the Military increased the most at 36.6% while that of Farming, Forestry and Fishing decreased the most at 17.5%. The coefficient of variation also increased for all

Table 2a: Occupation								
	Mean			Coefficient of Variation			Gini Coefficient	
Occupation	1990	2004	% change	1990	2004	% change	1990	2004
Executive, Administrative and Managerial	3990.0	5012.6	14.3%	0.7	1.0	48.3%	0.36	0.42
Professional Specialty	3560.6	3902.9	9.6%	0.6	1.1	68.5%	0.35	0.44
Technicians and Related Support	2934.7	2602.3	-11.3%	0.6	0.9	49.9%	0.33	0.37
Sales	2137.6	2381.1	11.4%	1.1	1.6	50.2%	0.52	0.6
Administrative Support	1870.2	2025.4	8.3%	0.7	0.9	34.8%	0.36	0.40
Private Household	757.2	938.3	23.9%	0.9	1.0	10.9%	0.47	0.51
Protective Service	2643.4	2724.5	3.1%	0.7	0.7	4.3%	0.39	0.4
Other Service (not private or protective)	1104.9	1111.8	0.6%	0.8	0.9	13.9%	0.43	0.47
Farming, Forestry and Fishing	1239.0	1021.8	-17.5%	1.1	1.7	50.8%	0.51	0.59
Precision Production, Craft and Repair	2766.9	2566.2	-7.3%	0.6	0.7	24.6%	0.32	0.38
Machine Operators, Assemblers and Inspectors	1994.4	2312.3	15.9%	0.7	0.8	22.8%	0.35	0.38
Transportation and Material Moving	2424.5	2476.2	2.1%	0.7	0.9	32.7%	0.37	0.44
Handlers, Equipment Cleaners, Helpers, and Laborers	1418.7	1718.3	21.1%	0.9	1.2	35.9%	0.45	0.44
Military	2931.6	4004.5	36.6%	0.5	0.9	63.9%	0.25	0.37
Aggregate	2415.2	2760.4	14.3%	0.8	1.2	43.1%	**0.43**	**0.49**
	% of total employed							
Occupation	1990	2004	%-point change					
Executive, Administrative and Managerial	11.6%	11.6%	0.0%					
Professional Specialty	12.5%	19.5%	7.0%					
Technicians and Related Support	3.7%	1.6%	-2.1%					
Sales	11.2%	8.8%	-2.4%					
Administrative Support	17.6%	17.7%	0.1%					
Private Household	0.6%	1.8%	1.2%					
Protective Service	1.8%	2.3%	0.5%					
Other Service (not private or protective)	12.1%	11.2%	-0.9%					
Farming, Forestry and Fishing	1.5%	1.0%	-0.5%					
Precision Production, Craft and Repair	10.1%	11.0%	0.9%					
Machine Operators, Assemblers and Inspectors	7.1%	5.7%	-1.4%					
Transportation and Material Moving	4.5%	3.5%	-1.0%					
Handlers, Equipment Cleaners, Helpers, and Laborers	4.7%	3.0%	-1.6%					
Military	1.0%	1.0%	-0.1%					
Aggregate	100.0%	99.7%	---					

occupations (43.1% at the aggregate level), with the largest increase seen in Professional Specialty at 68.5%.

The Gini coefficient also increased for all occupations except Handlers, Equipment Cleaners, Helpers and Laborers, who showed a slight decrease from 0.45 to 0.44. Sales had the highest coefficient in 1990 (0.52), and it continued to have the highest in 2004 (0.60), though this is not surprising as we would expect that a large portion of salespeople's income to be based on commission, which could vary widely from person to person based on experience and reputation. Farming, Forestry and Fishing also had high Gini coefficient in 1990 (0.51), and it increased significantly by 2004 (to 0.59). As already mentioned, however, we would expect much of this increase to be attributable to the inclusion of capital gains in their reports of earnings, which would skew the earnings of these individuals. I also calculate the percentage of the workforce each occupation constitutes in each year. Most of the occupations shrank slightly, while the rest grew slightly. The only big change was Professional Specialty, which grew 7.0%. Interestingly, this was accompanied by one of the largest increases in the Gini coefficient from 0.35 to 0.44 (second only to the military, which increased from 0.25 to 0.37).

In Table 2b, I calculate the aggregate Gini coefficient by multiplying the Gini coefficient for each occupation by the percentage of the workforce it constitutes for each year and taking their sum. Similar to the industry tables, the Gini coefficients I calculate in the second occupation table, which are weighted by employment, are slightly lower than the coefficients I calculated in the first table, which are weighted by income. In fact, there is an even bigger disparity between the two weighted measurements (0.3862 compared with 0.43, and 0.4370 compared with 0.49) when we slice the workforce by

Table 2b: Occupation Breakdowns											
Check			Over time			Aggregate Gini Coefficient-assume no within-occupation inequality					
With own year weights			With opposite weights, base year 1990			Using a simulated population of 1000					
1990	2004		Shares change	Inequality changes		1990	2004				
0.0417	0.0488		0.0418	0.0486		0	0				
0.0438	0.0860		0.0684	0.0550		0	0				
0.0121	0.0058		0.0051	0.0136		0	0				
0.0580	0.0527		0.0457	0.0670		0	0				
0.0635	0.0709		0.0638	0.0705		0	0				
0.0027	0.0092		0.0085	0.0029		0	0				
0.0070	0.0090		0.0088	0.0072		0	0				
0.0521	0.0528		0.0483	0.0570		0	0				
0.0078	0.0061		0.0053	0.0090		0	0				
0.0324	0.0418		0.0352	0.0384		0	0				
0.0250	0.0217		0.0200	0.0271		0	0				
0.0165	0.0154		0.0129	0.0196		0	0				
0.0210	0.0133		0.0136	0.0205		0	0				
0.0026	0.0035		0.0024	0.0038		0	0				
0.3862	**0.4370**		**0.3798**	**0.4404**		**0.21**	**0.24**				
Two calculations for within-occupation inequality growth:											
Total change - between-occupation change = within-occupation change					*0.0572*	106.4%					
Total change - within-occupation change = between-occupation change					-0.0034	-6.4%					
Weighted within-occupation change					*0.0542*	113.3%					
Weighted between-occupation change					-0.0064	-13.3%					

occupation. We can say, then, that weighting by employment deflates the Gini coefficient because more weight is put on occupations that are relatively more equal. This effect is even more dramatic for occupation estimates than it is for industry estimates of inequality because the change in the occupational structure actually contributed to a decrease in overall earnings inequality.

I then use the same two methods I used in Table 1b to calculate the change in within- and between-occupation inequality over time. In both cases, I find that the change in within-occupation inequality *more* than accounts for the change in total inequality, and that the between-occupation inequality actually decreases from 1990 to 2004, which works to deflate total inequality from 1990 to 2004. In the third column, I again create a simulated population of 1000 in which all the workers of each occupation earn the mean for that occupation (i.e. for 1990, 116 people earn $3990.0, 125 people earn $3560.6, 37 people earn $2934.7, etc.) in order to assume no within-occupation inequality. Again, the aggregate Gini coefficient that I calculate to represent the contribution of between-occupation inequality to total inequality is small (0.21 compared to 0.43, and 0.24 compared to 0.49). Because a changing occupational structure actually resulted in *decreases* to between-group inequality, it seems to be even less an explanation for the increase in total inequality than industrial structure changes.

Gender Breakdown

In Table 3, I calculate the mean, coefficient of variation, and the Gini coefficient of earnings for men and women classified under each occupation, as well as the percentage of the total workforce that men and women constitute in each occupation for each year. At the aggregate level, both men and women saw an increase in real earnings:

Table 3: Sex by Occupation

	Mean						Coefficient of Variation						Gini Coefficient			
	1990		2004		% change		1990		2004		% change		1990		2004	
Occupation	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Executive, Administrative and Managerial	4849.5	2963.6	6063.8	3815.1	25.0%	28.7%	0.6	0.6	1.0	0.8	63.2%	26.6%	0.34	0.33	0.42	0.38
Professional Specialty	4390.1	2929.3	5127.4	3047.7	16.8%	4.0%	0.6	0.6	1.1	0.9	82.0%	44.9%	0.33	0.33	0.43	0.40
Technicians and Related Support	3458.3	2380.0	3441.2	2388.9	-0.5%	0.4%	0.6	0.6	1.3	0.7	109.6%	17.8%	0.32	0.30	0.42	0.34
Sales	3128.2	1302.3	3483.2	1520.5	11.3%	16.8%	0.9	1.1	1.4	1.5	62.6%	46.0%	0.44	0.50	0.55	0.58
Administrative Support	2394.7	1743.2	2496.5	1890.9	4.3%	8.5%	0.7	0.6	1.1	0.8	53.5%	22.6%	0.39	0.34	0.44	0.37
Private Household	1840.3	736.8	1129.5	909.2	-38.6%	23.4%	0.4	0.9	1.0	1.0	165.5%	10.1%	0.18	0.47	0.51	0.50
Protective Service	2809.5	1836.2	2951.2	1943.9	5.0%	5.9%	0.7	0.9	0.7	0.9	3.7%	-3.5%	0.36	0.49	0.38	0.46
Other Service (not private or protective)	1228.2	1031.0	1274.9	973.3	3.8%	-5.6%	0.8	0.8	0.9	0.9	13.7%	9.7%	0.44	0.42	0.48	0.45
Farming, Forestry and Fishing	1372.7	729.0	1138.7	668.1	-17.0%	-8.3%	1.1	0.9	1.7	1.4	53.7%	50.6%	0.49	0.51	0.56	0.68
Precision Production, Craft and Repair	2849.8	1923.5	2644.7	1929.7	-7.2%	0.3%	0.6	0.6	0.7	0.8	25.1%	29.4%	0.31	0.33	0.37	0.40
Machine Operators, Assemblers and Inspectors	2388.3	1497.9	2632.9	1580.5	10.2%	5.5%	0.6	0.6	0.8	0.7	30.4%	9.0%	0.32	0.34	0.34	0.36
Transportation and Material Moving	2513.7	1540.1	2634.1	1462.4	4.8%	-5.0%	0.7	0.9	0.9	0.8	34.5%	-11.9%	0.36	0.44	0.42	0.43
Handlers, Equip. Cleaners, Helpers and Laborers	1480.4	1141.5	1792.0	1441.3	21.0%	26.3%	0.9	0.8	1.1	1.4	31.0%	69.6%	0.45	0.43	0.43	0.46
Military	2931.6	2699.8	4123.8	3118.5	40.7%	15.5%	0.5	0.4	0.9	0.6	65.1%	48.8%	0.25	0.23	0.36	0.35
Aggregate	2934.5	1866.7	3336.7	2179.6	13.7%	16.8%	0.8	0.8	1.2	1.0	53.8%	27.5%	**0.41**	**0.42**	**0.48**	**0.47**

	% of total employed					
	1990		2004		%-point change	
Occupation	Men	Women	Men	Women	Men	Women
Executive, Administrative and Managerial	6.3%	5.3%	5.9%	5.2%	-0.4%	-0.1%
Professional Specialty	5.4%	7.1%	8.0%	11.5%	2.6%	4.4%
Technicians and Related Support	1.9%	1.8%	0.8%	1.3%	-1.1%	-0.4%
Sales	5.1%	6.1%	3.9%	4.9%	-1.3%	-1.1%
Administrative Support	3.4%	14.2%	3.9%	13.8%	0.5%	-0.4%
Private Household	0.0%	0.6%	0.7%	1.7%	0.7%	1.2%
Protective Service	1.5%	0.3%	1.8%	0.5%	0.3%	0.2%
Other Service (not private or protective)	4.5%	7.6%	4.9%	6.0%	0.4%	-1.6%
Farming, Forestry and Fishing	1.2%	0.3%	0.7%	0.3%	-0.5%	0.0%
Precision Production, Craft and Repair	9.2%	0.9%	9.8%	1.2%	0.6%	0.3%
Machine Operators, Assemblers and Inspectors	4.0%	3.2%	4.0%	1.7%	0.0%	-1.4%
Transportation and Material Moving	4.0%	0.4%	3.0%	0.5%	-1.0%	0.1%
Handlers, Equip. Cleaners, Helpers and Laborers	3.8%	0.8%	2.3%	0.6%	-1.5%	-0.2%
Military	0.9%	0.1%	0.4%	0.1%	-0.5%	0.0%
Aggregate	51.4%	48.6%	50.2%	49.5%	-1%	1%

13.7% for men, 16.8% for women. The coefficient of variation also increased for both groups: 53.8% for men, 27.5% for women. The Gini coefficient was about the same for men and women in 1990 (0.41 or men, 0.42 for women) and it increased by almost the same amount to the level in 2004 (0.48 for men, 0.47 for women). Women gained slightly more ground than men in terms of their percentage of the total employed (a 1% increase from 1990 to 2004, whereas the men's share decreased 1%).

My original hypothesis was that an increasing percentage of women chose to enter the workforce which, when paired with the fact that they were more likely to be less educated and less experienced than men, would increase aggregate inequality, and that the change in inequality would be higher for women than it would be for men. This hypothesis turns out to be false, however, as we see that the percentage growth of women employed is quite small; if McNeil's findings of the size of growth in the presence of women in the workforce are accurate, then we must conclude that the size of this growth had more or less tapered off by 1990. Even comparing men's and women's aggregate Gini coefficients does not support this notion that women's participation in the labor force has added to growth in total inequality as the increase in earnings inequality was slightly higher for men than for women. It is possible that a continued increasing percentage of women entering the workforce would have more of an impact on total inequality, but from my calculations here, sex does not seem to be a sufficient explanatory variable.

Racial Breakdown

In Table 4, I calculate the mean, coefficient of variation, and the Gini coefficient of earnings for each race at the aggregate level. The mean of real earnings increased for

Table 4: Race												
	Mean											
	1990				2004				% change			
Work force	White	Black	Asian	Other	White	Black	Asian	Other	White	Black	Asian	Other
Aggregate	2482.1	1962.6	2603.8	1765.9	2847.9	2184.7	3384.9	2114.2	14.7%	11.3%	30.0%	19.7%
	Coefficient of Variation											
	1990				2004				% change			
Work force	White	Black	Asian	Other	White	Black	Asian	Other	White	Black	Asian	Other
Aggregate	0.8	0.8	0.8	0.9	1.2	1.2	1.2	1.1	41.9%	55.5%	54.8%	16.9%
	Gini Coefficient											
	1990				2004							
Work force	White	Black	Asian	Other	White	Black	Asian	Other				
Aggregate	0.43	0.4	0.4	0.45	0.49	0.45	0.49	0.48				
	% of total employed											
	1990				2004				%-point change			
Work force	White	Black	Asian	Other	White	Black	Asian	Other	White	Black	Asian	Other
Aggregate	83.9%	12.8%	2.8%	0.5%	81.0%	11.9%	3.4%	3.7%	-3%	-1%	1%	3%

all races, with the largest increase going to the Asian workers at 30.0%. The coefficient of variation also increased for all groups. The percent change for the Other workers was moderate (16.9%), while the percent changes for the White, Black and Asian workers were much higher (41.9%, 55.5%, and 54.8%, respectively). The Gini coefficient also increased for all groups, though the Asian workers had a relatively low coefficient in 1990 (0.40), and it increased to be the largest coefficient in 2004 (0.49). The coefficient for the Other workers (0.45 in 1990) remained high in 2004 as it increased to 0.48. In terms of the percentage each race made up of the total workforce, the White workers' share decreased 3% and the Black workers' share by 1%, while the Asian workers' share increased by 1% and the Other workers' share by 3%. These percentages are consistent with the percentage of total adults in the U.S. between 1990 and 2004. It is a bit ambiguous who makes up the Other workers, but given that "Latino" is added to the 2004 SIPP Data Dictionary under this race variable, it is safe to assume a rather large increase in these workers. If the shares of Asian and Other workers continue to increase, it is probable that the inequality for these groups would also continue to increase, which in turn would pull up total inequality as well.

Educational Breakdown

In Table 5, I calculate the mean, coefficient of variation, and the Gini coefficient of earnings for different education levels, as well as the percentage of the total employed and total adults that each education level constitutes each year. The mean of real earnings for workers who finished high school and those who went to college and beyond (hereafter called "high school graduates" and "college+ graduates"), increased significantly (0.5% for high school graduates, 9.6% for college+ graduates). The mean of

Table 5: Education Level									
	Mean								
	1990			2004			% change		
Work force	Less than high school	High school	College +	Less than high school	High school	College +	Less than high school	High school	College +
Aggregate	1600.4	2090.8	3059.4	1468.1	2100.5	3353.1	-8.3%	0.5%	9.6%
	Coefficient of Variation								
	1990			2004			% change		
Work force	Less than high school	High school	College +	Less than high school	High school	College +	Less than high school	High school	College +
Aggregate	0.8	0.7	0.8	1.1	1.0	1.1	37.2%	43.5%	43.9%
	Gini Coefficient								
	1990			2004					
Work force	Less than high school	High school	College +	Less than high school	High school	College +			
Aggregate	0.41	0.41	0.41	0.51	0.44	0.44			
	% of total employed								
	1990			2004			%-point change		
Work force	Less than high school	High school	College +	Less than high school	High school	College +	Less than high school	High school	College +
Aggregate	12.7%	37.3%	50.0%	8.5%	26.2%	65.3%	-4%	-11%	15%

real earnings for workers who did not finish high school, on the other hand, decreased significantly (8.3%) between 1990 and 2004. The coefficient of variation increased for all groups by at least 35%. The Gini coefficient in 1990 was the same for all groups (0.41), and it increased for all groups by 2004. The increase for high school graduates and college+ graduates was the same (0.44), but the increase for workers who did not finish high school was much higher (0.51).

This supports the theory, then, of an increasing demand for skilled labor, though this increasing demand for educated workers would have to span all industries and occupations to make the shifts in these structures insignificant to the changes in total inequality. This casts doubt on Weinberg's assertion that one factor of increasing total inequality is the shift in employment from those goods-producing industries that have disproportionately provided high-wage opportunities for low-skilled workers, towards services that disproportionately employ college graduates, and towards low-wage sectors such as retail trade. It seems that across the board it became increasingly necessary to be educated in order to have a job and earn a higher real wage: in terms of the total workforce, the least educated workers' share decreased 4%, the high school graduates' share decreased 11%, and the college+ graduates' share increased 15%. In addition, because the high school graduates' share decreased rather dramatically compared to the change in the least educated workers' share, we can say that there was a higher disparity between the highly educated workers (college+ graduates) and the least educated workers, where the former experienced substantial real gains in earnings, and the latter experienced significant real losses (the middle group's real earnings remained about the same, but its size significantly decreased).

Labor Union Participation Breakdown

In Table 6, I calculate the mean, coefficient of variation, and the Gini coefficient of real earnings based on coverage by a labor union contract, as well as the percentage of the total workforce that was covered by such a contract in each year. As we would expect, the workers who were covered by a labor union contract earned higher real wages than the workers who were not covered by such a contact. Interestingly, however, the percentage increase in real earnings was almost exactly the same for both groups between 1990 and 2004 (approximately 20%). The mean of unionized workers continued to be significantly higher than that of non-unionized workers, but the gap between them widened only slightly for the time period I investigated; indeed, in both 1990 and 2004, non-unionized workers on average earned about 83% of unionized workers' earnings. Also not surprisingly, the variation around the mean was much higher for the non-unionized workers than those covered by a union contract (0.9 compared with 0.6), though the difference in the change of this coefficient was smaller (43.8% compared with 32.2%). Likewise, the relationship between the changes in the Gini coefficient was similar to the relationships already discussed. In 1990, the Gini coefficient for unionized workers was significantly lower than that for their non-unionized counterparts (0.33 compared 0.45). By 2004, the Gini coefficient had increased for both groups, though by a larger amount for the non-unionized workers (0.36 compared with 0.50).

I also calculate the percentage of workforce membership in labor unions constitutes for both years. By 1990, only 13.7% of the workforce was unionized compared to higher percentages of the 1970s and 80s, but this figure further decreased by 2004 to just 6.3%. To determine whether the increase in total earnings inequality has been due to the dying out of labor unions (between-coverage status inequality) or to

Table 6: Coverage by Labor Union Contract																
	Mean						Coefficient of Variation						Gini Coefficient			
	1990		2004		% change		1990		2004		% change		1990		2004	
Work force	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Aggregate	2758.1	2294.4	3305.8	2725.6	19.9%	18.8%	0.6	0.9	0.9	1.3	32.2%	43.8%	**0.33**	**0.45**	**0.38**	**0.50**
	% of total employed															
	1990		2004		%-point change											
Work force	Yes	No	Yes	No	Yes	No										
Aggregate	14.3%	85.7%	6.9%	92.9%	-7%	7%										
Check			Over time													
With own year weights			With opposite weights, base year 1990													
1990	2004		Shares change	Inequality changes												
0.0473	0.0264		0.0229	0.0545												
0.3855	0.4645		0.4181	0.4283												
0.4328	**0.4909**		**0.4410**	**0.4828**												
Two calculations for within-industry inequality growth:																
Total change - between-industry change = within-coverage status change					*0.0499*	86.0%										
Total change - within-industry change = between-coverage status change					0.0081	14.0%										
Weighted within-coverage status change					*0.0500*	85.9%										
Weighted between-coverage status change					0.0082	14.1%										

increases in the Gini coefficient within each group (within-coverage status inequality), I repeat the thought experiment of the industry and occupation tables to break down total earnings inequality. I find that the increase in total inequality was largely attributable to an increase in within-coverage status inequality (which accounted for ~85% of the increase in total inequality), with a slight contribution from an increase in between-coverage status inequality. We can say then that the classical notion that labor unions effectively decrease earnings inequality, at a higher cost, is validated: the unionized workers on average earned more than their non-unionized counterparts and there was less inequality between them.

Age Breakdown

In Table 7, I calculate the mean, the coefficient of variation, and the Gini coefficient of real earnings for different age groups, as well as the percentage of the total workforce that each age group constitutes each year. For each year, the mean of real earnings increases as workers age, reaches a maximum, and then decreases as workers age after this point. In 1990, this maximum of real earnings was experienced by workers between 40 and 49 years old. In 2004, the maximum of real earnings was experienced later, for workers between 50 and 59 years old. The difference in timing of this maximum could be due to a higher life expectancy or a trend of later retirement, or it could be indicative of a higher volatility of the life cycle of earnings. Overall, the mean of real earnings increased for all age groups except for workers between 15 and 29 years old, who experienced a decrease in real earnings of 3.7%. The workers who had the largest increase were the 50-59-year-olds with an increase of 21.2% (all the other age groups had increases of approximately 10%). The coefficient of variation also increased across all

Table 7: Age															
	Mean														
	1990					2004					% change				
Work force	15-29	30-39	40-49	50-59	60+	15-29	30-39	40-49	50-59	60+	15-29	30-39	40-49	50-59	60+
Aggregate	1632.3	2715.6	3092.4	2922.2	2100.7	1571.6	3038.7	3377.9	3537.9	2294.2	-3.7%	11.9%	9.2%	21.1%	9.2%
	Coefficient of Variation														
	1990					2004					% change				
Work force	15-29	30-39	40-49	50-59	60+	15-29	30-39	40-49	50-59	60+	15-29	30-39	40-49	50-59	60+
Aggregate	0.9	0.7	0.7	0.8	1.0	1.1	1.1	1.1	1.1	1.5	31.6%	44.9%	48.8%	44.8%	44.9%
	Gini Coefficient														
	1990					2004									
Work force	15-29	30-39	40-49	50-59	60+	15-29	30-39	40-49	50-59	60+					
Aggregate	0.45	0.38	0.39	0.40	0.50	0.50	0.44	0.44	0.45	0.57					
	% of total employed														
	1990					2004					%-point change				
Work force	15-29	30-39	40-49	50-59	60+	15-29	30-39	40-49	50-59	60+	15-29	30-39	40-49	50-59	60+
Aggregate	33.8%	27.9%	20.7%	11.8%	5.7%	26.8%	23.3%	25.1%	17.3%	7.4%	-7%	-5%	4%	5%	2%

the age groups, though it was the highest for workers over 60. Finally, the Gini coefficient increased across all age groups, though it was lower in both years for the middle age groups (approximately 0.40 to 0.44) than the youngest and oldest groups (0.45 to 0.50 for the youngest, and 0.50 to 0.57 for the oldest).

The fact that the oldest age group had a relatively high level of inequality for both years is not surprising, as we would expect a higher percentage of older workers to work part-time than other age groups as they prepare for complete retirement. Similarly, the presence of high inequality within the youngest age group could be explained by differences in education (in addition to a high level of part-time hours as some workers complete their education), which have more of an impact on earnings early on when a worker does not have references and experience to signal his real worth to the market. Finally, from this data we do not see a higher volatility of the life cycle of earnings as some other authors have suggested, as the average real earnings for all age groups increased by ~10% (except for the youngest workers, whose average decreased 3.7%, and the 50-59-year-olds, whose average increased by 21.2%), and the Gini coefficient for the middle age groups increased very little.

Evaluating the Remaining Theories

I have already discussed the merit of some of the existing theories of increasing income inequality, including women's entrance into the workforce, an increasing demand for skilled labor, changes in the industrial and occupational structures, changes in labor union participation, and a higher volatility of the life cycle of earnings. Several other explanations have been put forth to account for the increasing inequality of earnings, however, including the overall trend of globalization and increased immigration, changes in inflation and unemployment, changes in per-capita transfers, household composition changes, a decrease in real minimum wage, a heavier reliance on temporary workers, and a higher variance of hours worked. In this section, I will evaluate these remaining theories against the individual earnings data I have analyzed so far.

There is a wealth of literature on the impacts of globalization, including those on income inequality. Pikkety and Saez (2003), for example, argue that the classic inverse-U-shaped Kuznets curve, which traditionally rises with industrialization and later declines as more and more workers join the high-productivity sectors of the economy, has doubled back on itself. They contend that this is especially true in the United States, where a “new industrial revolution” took place in the 1970s, and thus, that the past 30 years have just been a remake of the previous inverse-U curve. It is possible that we have not reached the point where inequality is expected to decrease again yet, but it currently seems that globalization cannot be a large contributor to increasing income inequality. With the onset of globalization, we expect large shifts out of manufacturing and other goods-producing industries in developed countries as they are outsourced from cheaper locations. Indeed, I demonstrate that this shift actually did occur in the U.S. in Tables 1a and 1b. However, the increases in between-industry inequality had little, if any, significant impact on the increase in total earnings inequality; therefore, we cannot say that globalization has had a direct causal relationship with increasing income inequality. It is still possible that there could still exist indirect links between the two patterns, including increased immigration of more diligent and astute workers to developed countries and a heavier reliance on government intervention in certain industries that are known to suffer from the effects of globalization, but that hypothesis has yet to be tested in the economic literature.

Changing household composition is a trend that McNeil (1998) demonstrates in his work, one that he finds to have a significant impact on increasing earnings inequality in the U.S. between 1969 and 1996. Although I investigated data on individual earnings, I found no decrease in the percentage of workers employed based on the factors of sex, race, education, labor union participation, or age that contributed to an increase in earnings inequality, at least between groups. On the contrary, whenever a certain group shrunk in its percentage of the workforce, the change actually served to decrease between-group inequality. For example, as more White workers (who had the second highest mean of real earnings in 1990) left the workforce, their mean of real earnings increased only moderately when compared with the increases of the Asian and Other workers. This caused a convergence between the means of all the groups, which in turn lowered between-group inequality. Even though I did not find a correlation between the majority of the aforementioned characteristics and increasing earnings inequality, it is probable that McNeil’s claim on the importance of household composition, if there has been a significant change, is a valid one.

Much is made of the rising demand for skill and thus, the importance of education to ensure high earnings during this “new industrial revolution.” McNeil (1998) and Weinberg (1996) both discuss this theme. Like McNeil, I found an overall increase in the educational attainment levels of individuals regardless of their income position. However, unlike McNeil’s research, which demonstrates stagnant incomes for those below the median between 1969 and 1996, I found a real decrease in average earnings for workers that did not finish high school and a real increase in average earnings for workers that at least graduated from college. I also found, not surprisingly, that the percentage of highly educated adults of those that were employed was much higher, and increased at a higher rate between 1990 and 2004, than the percentage of adults who did not complete high school of those that were employed. Thus, I find that education (or other qualities that are correlated with education like diligence or natural intelligence) plays a significant role in determining whether a person will be employed, and how much that person will earn relative to its counterparts of different educational groups.

Several authors also cite a decrease in the real minimum wage as a cause of increasing earnings inequality. Indeed, the real federal minimum wage in 1990 was $5.49, compared with $5.15 in 2004,[10] a decrease of approximately 6%. Because I analyzed earnings and not wages, I am unable to comment on the effects of this phenomenon. However, the dataset I analyzed is quite capable of evaluating the related theory of a heavier reliance on temporary or part-time workers, which states that a heavier reliance on these workers has caused fewer workers (typically out of the low-earner group) to be hired on salary and thus, their real earnings are decreased. Indeed, I do find that the percentage of the labor force that worked less than 30 hours per week increased from 16% in 1990 to 22% in 2004, which gives some credence to this conjecture.

This argument corresponds to the hypothesis of an increased variance of hours worked between the top-earner workers and the low-earner workers. In Table 9, I calculate the mean, the coefficient of variation, and the Gini coefficient for the hours

[10] Both stated in 2004 dollars. The nominal minimum wage for 1990 was $3.80 after a 25% increase from the previous year's rate. Though the minimum wage applied to less than half of all workers before 1990, it now applies to more than 90% of private employees (some seasonal, domestic, and a few other types of workers are still exempt). Most states have minimum wage provisions, but they are usually no higher than the federal minimum.

worked per week for each income quintile. For each of the quintiles, the mean number of hours worked decreased from 1990 to 2004. For example, the average worker at middle 20% of the income distribution in 1990 needed to work 51.14 hours, whereas in 2004 he only needed to work 41.73 hours (a decrease of 18.4%). I also find that the coefficient of variation increases for each of the quintiles (74.8% for the middle 20%). Interestingly, the highest 20% of workers showed the biggest decrease in mean number of hours worked (22.3%) and the biggest increase in the coefficient of variation of those hours (833.1%). Finally, the Gini coefficient for the hours worked actually decreased slightly from 0.16 to 0.15, negating the hypothesis of a higher variance between the high and low earners. These findings, without accounting for differences in education and experience, support the argument of "unfair" hikes in the earnings of America's top earners, including its CEOs, since the average number of hours they worked actually decreased in relation to their lower-earning counterparts.

Table 9: Hours Worked by Earnings Quintiles

	Mean			Coefficient of Variation		
Earnings Quintile	1990	2004	% change	1990	2004	% change
Lowest 20%	38.258	35.46	-7.3%	0.31	0.47	52.2%
Low-Mid 20%	49.125	46.222	-5.9%	0.23	0.40	73.7%
Middle 20%	51.14	41.73	-18.4%	0.28	0.49	74.8%
High-Mid 20%	51.30	43.45	-15.3%	0.21	0.52	150.9%
Highest 20%	51.30	39.86	-22.3%	0.08	0.73	833.1%
Gini coefficient	**0.16**	**0.15**				

Effects on the Middle Class

So far we have looked at the overall income distribution to demonstrate how it became more unequal between 1990 and 2004. I have shown that the proportion of men and women in the workforce remained relatively unchanged. The proportion of Asian and

Other workers, on the other hand, increased due to immigration, and the inequality of earnings for these groups also increased. Now that we know what level of earnings inequality existed for the whole workforce for 1990 and 2004, we can examine the effects this rising inequality has on the middle class. In my analysis, I define the lower bound of the middle class to be 2*poverty level, and the upper bound to be 5*poverty level. These parameters are in a sense rather arbitrary, but for my purposes I just want to get a *sense* of the middle class to see how it changed during the 14-year period. I will compare the results for this restrictive definition of the middle class with those for a more expansive definition.

In Table 8, I calculate the real poverty level for each year in 2004 dollars and the real earnings per month at that level. I then show the lower and upper bounds of the middle class by my definition, as well as note the lowest real income that is topcoded for each year.[11] I find that in fact, the middle class shrunk by only a small amount, if at all. In 1990, I find that the middle class (using the poverty level for individual earnings) made up approximately 19% of the workforce, and in 2004, about 18%. However, it is perhaps more intuitive to classify households as middle class rather than individuals, because even those who do not work at all are still afforded the benefits of being middle class if their total household earnings are at a certain level. Therefore, I complete the same calculations using the poverty level for household earnings. Here we find a bit more of a dramatic decrease in the size of the middle class. In 1990, we find that the middle class made up approximately 39% of the workforce, and in 2004, about 35%. For both

[11] As we would expect, in neither case were the incomes of the middle class workers higher than the topcoding threshold.

Table 8: Is the Middle Class Shrinking?								
Restrictive Definition								
individual	REAL	poverty	povmonth	topcoding	low end	high end	middle class %	Gini
	1990	9614.10	801.17	12044	1602.35	4005.87	19.08%	0.14
	2004	9827.00	818.917	12500	1637.83	4094.58	18.08%	0.15
household	REAL	poverty	povmonth	topcoding	low end	high end	middle class %	Gini
	1990	13359.00	1113.25	48175	2226.50	5566.25	38.69%	0.14
	2004	19484.00	1623.67	50000	3247.33	8118.33	35.31%	0.15
Expanded Definition								
individual	REAL	poverty	povmonth	topcoding	low end	high end	middle class %	Gini
	1990	9614.10	801.17	12044	1602.35	6409.40	24.58%	0.21
	2004	9827.00	818.917	12500	1637.83	6551.33	23.91%	0.21
household	REAL	poverty	povmonth	topcoding	low end	high end	middle class %	Gini
	1990	19307.69	1608.97	48175	3217.95	12871.79	27.22%	0.20
	2004	19484.00	1623.67	50000	3247.33	12989.33	26.29%	0.21
	1990	2004	%-point change					
White	84%	81%	-3%					
Black	13%	12%	-5%					
Asian	3%	3%	7%					
Other	0%	4%	853%					
Men	53%	51%	-5%					
Women	47%	49%	6%					

individuals and households, the Gini coefficient is quite small (0.14 in 1990, and 0.15 in 2004), which we would expect.

The upper bound of this definition of the middle class seems rather restrictive, however, so I expand it to 8*the poverty level and recalculate the mean and the share of the total for the middle class. Again I find that the middle class shrank less than 1% for both individuals and households, and that the Gini coefficient remained unchanged at

0.20. I also examine how the characteristics of sex and race have changed for the middle class between 1990 and 2004. For example, fewer White and Black workers made up the middle class in 2004, while the Asian workers' share increased 7%, and the Other workers' share increased a whopping 858%. The last figure is probably exaggerated due to a small sample size in 1990, but I think it is still safe to assume a dramatic increase for these workers. Interestingly, women also increased their presence in the middle class by 6%, while men decreased theirs by 5%, which suggests that female workers in 2004 had higher education levels and/or more experience than their 1990 counterparts, which allowed them higher wages.

Conclusions

In this study of increasing earnings inequality in the U.S. between 1990 and 2004, I find that the increase was not due to changes in the industrial or occupational structures, and that in some cases these changes, in fact, led to decreases in total inequality. This suggests that the problem of increasing income inequality is not a benign one; the classical notion of workers being free to move between industries and occupations does not explain why income inequality continued to rise. In addition, I do not find globalization to be a direct cause of increasing income inequality. I also find that there was no evidence of an increased presence of women in the workforce or a higher variance of hours worked between high earner and low earner workers that could help explain the increase in inequality. I find more promising explanations in the rising demand for skill, the importance of education, and a higher reliance on part-time workers, though other researchers will need to validate these findings. More research should also be conducted to determine an optimal level of income inequality for the U.S., as it is not clear to what extent income inequality negatively affects society. This will require a more developed understanding of both the causes and effects of income inequality, but will surely help shape better policies and social norms that affect income distribution.

References

Acemoglu, Daron. “Technical Change, Inequality, and the Labor Market.” *Journal of Economic Literature*. 40 (March 2002): 7-72.

Atanasio, Orazio et al. “From Earnings Inequality to Consumption Inequality.” *The Economic Journal*. 112 (March 2002): C52-C59.

Banerjee, A. and A. Newman. “Occupational Choice and the Process of Development.” *Journal of Political Economy*. 101 (1993): 274-98.

Berman, Eli, John Bound, and Zvi Griliches. “Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufactures.” *Quarterly Journal of Economics*. 109, 2 (May 1994): 367-97.

Blau, Francine D. and Lawrence M. Kahn. “Swimming Upstream Trends in the Gender Wage Differential in the 1980s.” *Journal of Labor Economics*. 14, 4 (October 1996): 1-42.

Brown, Christopher. “Does Income Distribution Matter for Effective Demand? Evidence from the United States.” *Review of Political Economy*. Volume 16, Number 3 (July 2004): 291-307.

Burtless, Gary. “Comments on ‘Has U.S. Income Inequality Really Increased?’ by Alan Reynolds.” The Brookings Institution. 11 January 2007: 1-8.

Cleveland, Robert W. “Alternative Income Estimates in the United States: 2003.” *Current Population Reports*. U.S. Census Bureau. P60-228 (June 2005): 1-24.

Deininger K. and L. Squire. “Economic Growth and Income Inequality: Reexamining the Links.” *Finance and Development*. 34 (1997) 38-41.

Greenwood, J. and B. Jovanovic. “Financial Development, Growth, and the Distribution of Income.” *Journal of Political Economy*. 98 (1990): 1076-107.

Jenkins, Stephen P. and Philippe Van Kerm. “Trends in income inequality, pro-poor income growth, and income mobility.” *Oxford Economic Papers 58* (2006), 531-548.

Johnson, David S. and Stephanie Shipp. “Inequality and the business cycle: a consumption viewpoint.” *Empirical Economics*. 24 (1999): 173-180.

Karoly, L. (1993) “The trend in inequality among families, individuals and workers in the United States: a twenty-five year perspective.” *Uneven Tides: Rising Inequality in America*. Eds. S. Danziger and P. Gottschalk. Russell Sage Foundation, New York, 19-97.

Kruegger, Dirk and Fabrizio Perri. “Does Income Inequality Lead to Consumption Inequality? Evidence and Theory.” *Review of Economic Studies*. 73 (2006): 163-193.

Lee, David. “Wage Inequality in the United States during the 1980s: Rising Dispersion or Falling Minimum Wage?” *Quarterly Journal of Economics*. 114 (August 1999): 977-1023.

Lemieux, Thomas. “Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill?” *American Economic Review*. June (2006): 1-56.

Li, Hongy and Heng-fu Zou. “Income Inequality is not Harmful for Growth: Theory and Evidence.” *Review of Development Economics*. 2, 3 (1998): 318-334.

McNeil, John. “Changes in Median Household Income: 1969 to 1996.” *Current Population Reports*. U.S. Census Bureau. P23-196 (July 1998): 1-9.

Perotti, R. “Political Equilibrium, Income Distribution, and Growth.” *Review of Economic Studies*. 60 (1993):755-76.

Piketty, Thomas and Emmanuel Saez. “Income Inequality in the United States: 1913-1998.” *The Quarterly Journal of Economics*. CXVIII (Feb 2003): 1-37.

Weinberg, Daniel H. “A Brief Look at Postwar U.S. Income Inequality.” *Current Population Reports*. U.S. Census Bureau. P60-191 (June 1996): 1-4.

Winslow-Bowe, Sarah. “The Persistence of Wives’ Income Advantage.” *Journal of Marriage and Family*. 68 (November 2006): 824-842.

Wolff, Edward N., Ajit Zacharias and Asena Caner. “Household wealth, public consumption and economic well-being in the United States.” *Cambridge Journal of Economics*. 29 (2005): 1073-1090.