UKCPR
University of Kentucky
Center for
Poverty Research

Discussion Paper Series
DP 2008-08

ISSN: 1936-9379

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Christopher Bollinger
University of Kentucky
Department of Economics

James P. Ziliak
University of Kentucky
Department of Economics
Center for Poverty Research

December 2008

Preferred citation

Bollinger, C., and Ziliak, J. (2008, December). Changes in the distribution of income among single mother families: Murphy Brown meets inequality. *University of Kentucky Center for Poverty Research Discussion Paper Series,* DP2008-08.

Author correspondence: James P. Ziliak, University of Kentucky, Department of Economics, 335S Gatton Building, Lexington, KY 40506-0034. E-mail: jziliak@uky.edu. Phone: 859-257-2776.

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Christopher Bollinger
Department of Economics
University of Kentucky

James P. Ziliak
Department of Economics
Center for Poverty Research
University of Kentucky

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* Address correspondence to James P. Ziliak, Department of Economics, University of Kentucky, Lexington, KY 40506-0034; Email: jziliak@uky.edu; Phone: 859–257–2776. We thank Luis Gonzalez for excellent research assistance. We received many helpful comments on earlier versions of the paper from Becky Blank, Gary Burtless, Tom Deleire, Julia Isaacs, Thomas Lemieux, Austin Nichols, Belle Sawhill and seminar participants at Brookings Institution, Congressional Budget Office, and the Administration for Children and Families, U.S. Dept. of Health and Human Services, for helpful comments. Ziliak was a Visiting Fellow at the Brookings Institution while some of this research was conducted, and he thanks them for their generous hospitality. All errors are our own.

Changes in the Distribution of Income among Single Mother Families: Murphy Brown meets Inequality

Abstract: We document the demographic and economic forces underlying changes in income inequality among single mother families over the past three decades in the United States. Using decomposable measures of after-tax income-to-needs inequality, we examine within- and between-group inequality based on education attainment, age, past marital status, race, and employment status. We also conduct income factor decompositions to quantify the relative contributions of earnings, transfers, other income, and taxes to inequality. Our results from the March Current Population Survey show that income-to-needs inequality rose nearly 30 percent between 1979 and 2005. The demographic decompositions indicate that most of the change in inequality is occurring within groups, in part because of large, offsetting between-group changes in population shares and relative mean incomes. The most prominent economic factor underlying the rise in income inequality among single mother families is labor-market earnings, the latter of which was induced by rising variance of hourly wages.

Single mothers have been the subject of extensive social science research, beginning at least with the Moynihan Report in 1965, and more recently in the wake of major tax and welfare reforms that expanded the generosity of the Earned Income Tax Credit and created the new block-grant welfare program Temporary Assistance to Needy Families (Moffitt 2003; Ziliak (In press)).[1] The Moynihan Report expressed alarm over the growth of out-of-wedlock childbirth among young, low-educated African Americans, but in what turned out to be a prescient moment from popular culture, the composition of single mothers has changed dramatically in the ensuing decades. During the 1991-1992 television season the fictional character Murphy Brown, who was a highly educated and successful television journalist, chose to bear a child outside of marriage in what was characterized "as just another lifestyle choice." As shown in Table 1, between 1979 and 2005 the fraction of single mothers with at least 16 years of school doubled from 7 percent to 14 percent (and more than doubled for those with some college), the fraction never married rose from 18 percent to 43 percent, and the fraction over age 40 rose by one-third to 33 percent.[2] Thus, who becomes a single mother today compared to three decades ago is fundamentally different, and as highlighted by Grogger (2003) and Bollinger, et al. (In press), this changing demographic makeup has been associated with equally dramatic changes in the level and composition of income among single mothers. With few exceptions, however, there has been little research on the implications of these changes for the distribution of income among this population (Mills, et al. 2001; Schoeni and Blank 2000; Meyer and Sullivan 2006).

Documenting the sources of widening inequality in the United States continues to be a focal research priority. This vast literature has linked the growth in inequality to expanding

[1] The future Senator Daniel Patrick Moynihan was the lead author of a report entitled "The Negro Family: The Case for National Action," Office of Planning and Research, United States Department of Labor (March 1965), which later became known as the Moynihan Report. http://www.dol.gov/oasam/programs/history/webid-meynihan.htm
[2] Authors calculations based on selected years of the March Current Population Survey. Details on sample selection are given below in the Data Section.

college-high school premiums (Bound and Johnson 1992; Katz and Murphy 1992), rising returns to unobserved skills (Juhn, Murphy, and Pierce 1993), falling rates of unionization and the real value of the minimum wage (DiNardo, Fortin, and Lemieux 1996; Lee 1999), social norms (Piketty and Saez 2003), and the composition of the workforce (Lemieux 2006, 2008), among others. Much of the literature, and the complementary work on volatility (Gottschalk and Moffitt 1994; Dynarski and Gruber 1997; Haider 2001; Blundell, Pistaferri, and Preston 2006), has focused on men, and when women are considered, inequality among key subpopulations, notably single mothers, is not isolated.[3] This omission is somewhat surprising given that perhaps no other demographic group has been singled out more often by policy over the past three decades than single mothers with dependent children, including the welfare reforms of the 1980s and 1990s, along with the concomitant expansions of the Earned Income Tax Credit, Medicaid, and Supplemental Security Income (Moffitt 2003). Moreover, Lemieux (2006) recently showed that a substantial fraction of the increase in residual wage inequality can be attributed to changes in the composition of the workforce toward higher-educated and more-experienced workers. Comparing Table 1 here to Lemieux's (2006) Appendix Table 1 shows that the rate of growth in education attainment is faster among single mothers (both working and non-working) than among working women or men in general, suggesting that the demographic shift among single mothers may figure even more prominently in changes in inequality among this population.

In this paper we present new evidence on the demographic and economic forces underlying changes in income inequality among single mother families in the United States. Using data from the 1980-2006 waves of the March Current Population Survey, our focal measure of inequality is the squared coefficient of variation in disposable income-to-needs,

[3] Keys (2007) is among the first to examine women in the volatility literature. See Schmidt (2007) for a recent study on nonmarital childbearing among single women.

which is a member of the generalized entropy class of inequality measures and has several desirable properties that foster inequality decompositions (Shorrocks 1980, 1982; Mookherjee and Shorrocks 1982; Jenkins 1995). Our results show that there has been a secular increase in inequality of nearly 30 percent among all single mothers over the past few decades. Although the rise in inequality affected all major subgroups of single mothers, we show that it is has been concentrated in the upper tail of the income distribution since the early 1990s, which corroborates other recent work on inequality (Piketty and Saez 2003; Autor, et al. 2005).

We then examine the demographic and economic factors underlying the increase in inequality. To estimate whether the major between-group changes in education, age, and marital status translated into changes in inequality, or whether inequality of single mothers is largely determined within groups, we consider sub-group inequality decompositions based on education attainment, age, marital status, race, and employment status. The squared coefficient of variation is advantageous in this case because it is additively decomposable both at a point in time and over time into within-group and between-group inequality. This adding-up property is not guaranteed with more typical measures of inequality such as the Gini coefficient, the variance of log income, or 90-10 ratios, nor is adding up guaranteed with commonly employed "shift-share" decompositions. Likewise, given the documented changes in the income composition of single mother families away from transfers and toward labor-market earnings (Grogger (2003); Bollinger, et al. (In press)), we conduct economic factor decompositions to examine the relative roles of earnings, transfers, other income, and taxes on income inequality. Again, the squared coefficient of variation is advantageous because it is defined even if some income factors are zero, such as earnings for non-workers or transfers for non-welfare recipients.

The results of our demographic decompositions indicate that the more than doubling of higher educated single mothers in recent decades—the so-called Murphy Brown effect—led to a large, disequalizing increase in inequality, but this increase was offset by an equally large decrease in relative mean incomes because a higher educated mother in 2005 does not place as high in the 2005 income distribution as a similarly educated mother did in 1979. Thus, most of the rise in inequality was due to increases within groups. At the same time, the income factor decompositions indicate that nearly all of the increase in income inequality among single mothers is attributable to rising earnings inequality, though the rise was tempered by the progressive income tax system including the EITC. We conclude our analysis by exploring the sources underlying the increase in earnings inequality, particularly whether the 80 percent rise in earnings variance in this period is attributable to increases in the variance of hours or hourly wages. We find that the rise in earnings variance is due to the rising conditional earnings variance of workers, especially the variance of hourly wages.

II. Decomposing Income Inequality

Our focal measure of inequality is a member of the generalized entropy class of inequality indices, which is given as

(1) $$I_\kappa = \frac{1}{\kappa(\kappa-1)}\frac{1}{n}\sum_{i=1}^{n}\left\{\left(\frac{y_i}{\bar{y}}\right)^\kappa - 1\right\}, \kappa \neq 0,1$$

where y_i is disposable income for family i, $\bar{y}$ is average disposable income, and κ reflects an 'aversion to inequality' with lower values implying greater aversion to inequality (Shorrocks 1980; Cowell 2000). Although a wide variety of inequality measures are available, the generalized entropy class has several desirable properties including that it satisfies the Pigou-Dalton principle of transfers so that it records a rank-preserving increase in inequality with transfers from a poor person to a less poor person, it is scale invariant which is useful for making inequality comparisons across groups and time, it has useful stochastic dominance properties for ranking income distributions (Fomby, et al. 1999), and perhaps most important for our purpose here, the generalized entropy class provides consistent and additively decomposable measures of inequality. These exact decompositions can be made by subpopulations such as employment status, education, age, and race to make inequality comparisons within and between groups (Mookherjee and Shorrocks 1982), and by income factors such as earnings and transfers both at a point in time and over time (Shorrocks 1982). More common measures such as the Gini coefficient, the Atkinson index, the variance of log income, or percentile ratios such as 90-10 are not additively decomposable and thus do not provide consistent decompositions across groups. For example, Cowell (1988) notes that it is possible with the log variance to have a change in the income distribution that leaves between group inequality constant, raises inequality within each group, and yet results in lower total inequality, which is clearly an undesirable property.

For our analyses we set $\kappa = 2$, which yields $I_2 = 0.5 * CV^2$ or one-half of the squared coefficient of variation (one-half of the ratio of the variance to the squared mean). Aside from the decomposability properties mentioned above a key advantage of I_2 is that this summary measure is still defined even when some of the income components used in factor-share decompositions are zero. This is important in our sample because many single mothers do not work, do not receive transfers, or do not have other forms of non-transfer, nonlabor income.

To control for changes in average family size, we deflate after-tax income by the family-size specific poverty threshold, yielding a measure of disposable income to needs inequality (Gottschalk and Danziger 2005). In addition, we net out life-cycle age effects by using the residual from an OLS regression of disposable income to needs on a quartic in age. For person i, $i = 1,\ldots, N$, at time period t, $t = 1,\ldots, T$, we estimate

(2) $$y_{it} = \alpha + \beta_1 age_{it} + \beta_2 age_{it}^2 + \beta_3 age_{it}^3 + \beta_4 age_{it}^4 + \varepsilon_{it},$$

where ε_{it} is a mean zero random error. Because the mean of the fitted OLS residual, $\bar{\hat{\varepsilon}}_{it}$, used in the denominator of equation (1) is zero, the residual-based version of I_2 is undefined. Thus, in order to ameliorate this shortcoming, we add to each residual the year-specific mean of the predicted dependent variable, $\hat{\varepsilon}_{it} + \bar{\hat{y}}_t$, which results in a non-zero mean but has no impact on the year-specific estimated variance.

A. Demographic Decompositions

The generalized entropy measure of inequality is particularly useful for our purposes here because it is additively decomposable into within-group and between-group contributions to inequality, and only depends on a few, easily obtained terms (Mookherjee and Shorrocks 1982):

(3) $$I_2 = \sum_{k=1}^{K} \omega_k \mu_k^2 I_{2,k} + \frac{1}{2} \sum_{k=1}^{K} \omega_k [\mu_k^2 - 1]$$

where the first term is within-group inequality and the second term is between-group inequality, and the three determinants are the group-specific population share ω_k (k = 1,…, K), the square of the relative mean income of group k to the overall mean, $\mu_k^2 \equiv \left(\frac{\bar{y}_k}{\bar{y}}\right)^2$, and the group-specific inequality $I_{2,k}$. We consider sub-group inequality decompositions based on education attainment, age, marital status, race, and employment status

The decomposition in equation (3) provides a snapshot at a point in time of the demographics determining inequality, but it does not address directly the underlying sources of *change* in inequality over time. A long standing approach in the inequality literature to examine changes in inequality is to adopt the so-called shift-share method that takes a given factor, say education, and asks questions such as ‘what would inequality be in 2000 if education attainment remained fixed at levels in 1980?’, or ‘what is the predicted inequality in 1980 if education attainment was at its 2000 level?’ (DiNardo, et al. 1996; Mills, et al. 2001; Autor, et al. 2005;

Lemieux 2006). This approach is attractive because it offers transparent counter-factual decompositions of income distributions. However, as argued by Mookherjee and Shorrocks (1982) it is less useful when there are multiple changes occurring simultaneously (as affected single mothers over the past two decades) because it is difficult to determine the relative importance of each factor to trend inequality, and the combined effects of the changes do not necessarily sum up to total inequality, i.e. it is possible to over- or under-explain trend inequality with shift-share analyses.

A preferred alternative is to adopt the decompositions described in equation (3) as it aggregates changes in demographic factors exactly into the changes in total inequality; that is, changes in within and between group inequality add up to changes in total inequality. We can then decompose the changes in within-group and between-group inequality by taking the difference in equation (3) between periods *t* and *t*+1 and rearranging to yield

(4) $\Delta I_2 = \sum_{k=1}^{K} \omega_k(t)\, \mu_k^2(t) \Delta I_{2,k} +$

$\sum_{k=1}^{K} \Delta\omega_k \mu_k^2(t+1)\left[I_{2,k}(t+1) + 0.5\right] \, + \, \sum_{k=1}^{K} \omega_k(t) \Delta\mu_k^2\left[I_{2,k}(t+1) + 0.5\right]$

which says that the change in inequality is due to (a) a change in within-group inequality (the first term), (b) a change in population shares (the second term), and (c) a change in relative mean income (the third term).[4] We present results for both cross-sectional inequality decompositions from equation (3), as well as decompositions over time using equation (4). For completeness we also present some shift-share decompositions to compare with the results from equation (4).

B. Income Factor Decompositions

As highlighted in Grogger (2003) and Bollinger, et al. (In press), there have been substantial changes in the level and composition of income among single mothers over the past

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[4] Mookherjee and Shorrocks (1982) note that there is an index number problem here in that the decomposition in equation (5) uses current period values of population shares and (*t*+1) values of inequality and income shares, but it is possible to reverse the order.

two decades. In order to assess whether this changing income composition affects trends in changes in inequality we decompose disposable income-to-needs into four major factors

(5) $$y_{it} \equiv earnings_{it} + transfers_{it} + other_{it} - taxes_{it},$$

where *earnings* refers to total labor market earnings in the family, *transfers* refers to income from government provided means-tested transfers, disability insurance, and food assistance programs, *other* refers to other nonlabor income from both public and private sources, and *taxes* refers to the sum of federal, state, and payroll tax payments inclusive of the refundable portion of the federal and state EITC. Shorrocks (1982) shows that the generalized entropy class of inequality measures is additively decomposable into the contributions of income factors such as described in equation (5), which implies that we can write I_2 as

(6) $$I_2 = \sum_{f=1}^{4} S_f,$$

where f = *earnings*, *transfers*, *other*, *taxes* and $S_f \equiv \rho_f \frac{\sigma_f}{\sigma_y} I_2$. The term ρ_f is the correlation coefficient between factor f and total disposable income to needs y, σ_f is the standard deviation of income factor f, and σ_y is the standard deviation of disposable income to needs. Note that the product of the correlation coefficient and the ratio of the standard deviations is simply the coefficient from a least squares regression of disposable income to needs on income factor f.

The advantage of I_2 is clear in equation (6) because the values of factor f may be zero for many households, e.g. zero earnings for nonworkers or zero transfers for non welfare recipients, and yet I_2 is still defined in these cases. Another advantage is that like the demographic analysis above, changes in income factors add up to changes in total inequality. Specifically in the case of determining how changes in income factors affect changes in inequality between any two periods t and t+1 we can rewrite equation (6) as

(7) $$\Delta I_2 = I_2(t+1) - I_2(t) = \sum_{f=1}^{4} \Delta S_f.$$

Equation (7) says that the change in inequality across any two years is simply the sum of changes in the factor components (Jenkins 1995).

III. Data

The data are from the 1980–2006 waves (1979–2005 calendar years) of the March Annual Social and Economic Study of the Current Population Survey (CPS). The unit of observation is families headed by single women between the ages of 16 and 54 with dependent children present under the age of 18. Single heads include never married women as well as those divorced, separated, or widowed. In a bid to minimize measurement error in some of our subgroup analyses we allocate each mother to one of forty-five five-year birth by education cohorts, where three separate education groups of less than high school, high school graduate, and more than high school are assembled, and drop cohort-education cells with fewer than 50 observations (Blundell et al. 1998).

The key variable of interest is after-tax family income-to-needs, defined as gross income less net tax payments relative to the family-size and year-specific poverty threshold. For our purpose gross income is the sum of family income and the imputed value of public food assistance programs. Family income is the same as that used in official Census Bureau calculations of poverty and inequality and includes earnings, Social Security (retirement, disability, and survivors benefits), Supplemental Security Income, Unemployment Insurance, workers' compensation, AFDC/TANF and other forms of public cash welfare, veterans' payments, pension income, rent/interest/dividend income, royalties, income from estates, trusts, educational assistance, alimony, child support, assistance from outside the household, and other income sources. We define earnings as total family earnings from wage and salary income, non-farm self employment, and farm self employment. Because the Census Bureau defines a family as two or more persons related by birth, marriage, or adoption, family earnings contains earnings of the mother as well as dependent children and other related adults such as a resident grandparent. It does not contain earnings of cohabiting partners or other non-family members in the household. We append to family income the (Census Bureau's) imputed dollar value of public food assistance programs, which includes the Food Stamp Program and the National School Lunch and Breakfast Programs.

To construct after-tax total income we subtract tax payments from gross income and add back refundable EITC income. Tax payments are the sum of Federal, state, and payroll taxes that are estimated for each family in each year using the NBER *TAXSIM* program. The *TAXSIM* module calculates Federal, state, and payroll marginal tax rates and tax payments using basic information on labor income, taxable nonlabor income, dependents, and certain deductions such as property tax payments and child care expenses.[5] The Federal and state taxes include the respective EITC code for each tax year and state, thus allowing for the possibility of negative tax payments. We assume that the family only bears the employee share of the payroll tax rate. To control for changes in average family size over the twenty-seven years of our sample, we deflate after-tax income by the family-size specific poverty threshold. Because the poverty thresholds are updated each year for inflation, the measure of income to needs is in real terms.[6]

If the respondent refuses to supply earnings or transfer information, then the Census Bureau uses a "hotdeck" imputation method to allocate income to those with missing data. Bollinger and Hirsch (2006) argue that including allocated data generally leads to an attenuation bias on estimated regression coefficients based on imputed data. Bollinger and Hirsch (2007)

[5] The CPS does not have information on certain inputs to the *TAXSIM* program such as annual rental payments, child care expenses, or other itemized deductions. We set these values to zero when calculating the tax liability.

[6] The U.S. poverty thresholds have been critiqued over the years on many dimensions (Citro and Michael 1995), including the quality of the adult equivalent scale used. All results presented here are robust to just deflating income by the personal consumption expenditure deflator and not for family size.

also show that, for women, there appears to be no selection bias for dropping employed women who fail to report earnings. Hence, we follow their recommendation and drop those mothers with allocated earnings or transfer income. In addition, Burkhauser, et al. (2007) recently showed that the Gini coefficient and 90-10 ratio are sensitive to income top coding in the CPS. Because the coefficient of variation, and thus I_2, is top sensitive, it is possible that our measure also is affected by top coding in the CPS. Prior to 1995 the CPS assigned top-coded data a common value (though this value varied across income sources, and at times, years), but starting in 1995 they assigned top-coded data the mean values of actual income based on broad demographic groupings (age, race, gender, education). We examined the extent of top coding across all the subcomponents of income in our sample of single mother families and in most years there were no top-coded observations. However, top coding became more prevalent beginning in 1998, which is consistent with Burkhauser, et al. results for earnings from the general population. Although top coding never affected more than 0.2 percent of the sample of single mother families in our sample, we believe a common convention post 1995 as pre 1995 is likely to be more robust, and thus we impose the pre-1995 top codes on all subsequent years for our main analysis.[7] We also delete about 0.7 percent of the sample who report negative or zero family incomes, yielding a total sample of 99,436 single female-headed families. Basic summary statistics are provided in Appendix Table 1.

IV. Trends in Income Inequality of Single Mothers, 1979–2005

Figure 1 provides a basic overview of the trends in the mean and variance of disposable income to needs for single mothers. Mean income rose 18 percent over our sample period, while the variance rose nearly 80 percent. Both series show secular increases through the 1980s, but accelerate dramatically in the 1990s, a period that coincides with a strong macroeconomic

[7] As shown below, top coding turns out to be an important issue, even for single mother families.

expansion, large expansions in the EITC, as well as state and federal welfare reforms. Changes in mean income for this population have been well documented in the welfare literature (Moffitt 2003; Grogger 2003; Bollinger, et al. (In Press)), but this is the first evidence on the trends in the variability of income of single mothers. However, the variance is not scale invariant and as both the mean and variance are rising, inequality as measured by I_2 will rise by less than the variance. This is shown in Figure 2 where trends in inequality for disposable income-to-needs are depicted. [8] We also present the 95 percent confidence interval for I_2 constructed from 100 replications of the nonparametric bootstrap.

Figure 2 shows a trend increase in inequality of nearly 30 percent from 1979 to 2005, but there were subperiods of increasing followed by decreasing inequality. From 1979 to 1987 inequality rose 42 percent, but then fell by 17 percent over the next five years by 1992. It then accelerated over the next five years, reaching a within-period peak in 1997, and then subsided in the ensuing years as mean income rose strongly as shown in Figure 1. Even though the I_2 is estimated precisely in each year, the 95 percent confidence interval depicted in the figure widens markedly in the mid 1990s reflecting the increased variance of income.

Before proceeding we return to the issue of top coding raised by Burkhauser, et al. (2007). In Figure 3 the series labeled "common top code" reproduces our original series in Figure 2, and the series labeled "changing top code" refers to our estimate of I_2 using the Census provided imputations post 1995. As Figure 3 indicates, top coding has no impact on measured inequality prior to 1995, but after 1995 the series using the Census-provided top codes is significantly more volatile. This is surprising because our prior was that top coding would not be important for the population of single mothers even after 1995, but the results clearly reject that

[8] The inequality trends in both the real income level series and the income to needs series are identical, but in most years the level of inequality is higher (but not statistically) once adjustments are made for family need standards.

prior and indicate that adopting a common top code is necessary. We note, however, that our choice of using the pre-1995 methods for dealing with top codes is likely to understate the rise in inequality relative to the case if we used the post-1995 imputation method for the entire series. The reason for this understatement is that as we show below there was strong growth in incomes in the upper tail of the distribution over the past decade that is being attenuated with the use of the fixed top code value.

Meyer and Sullivan (2006) also raise concerns about income reporting in the CPS, but their focus is on the lower tail of the distribution where they argue that income is mismeasured because of underreporting of transfer income, especially beginning in the mid 1990s. They show that income fell about 30 percent at the 2nd percentile across the 1993–1995 and 1997–2000 periods in the CPS, whereas consumption (as measured in the Consumer Expenditure Survey) was relatively stable. They conclude that consumption is a superior measure of well being.[9]

Although a comparison of income to consumption is beyond the scope of the current project, in Figure 4 we use our common top-coded series to depict various percentiles of the income to needs distribution from the 2nd percentile (p2) to the 99th percentile (p99). Like Meyer and Sullivan (2006) we do find a 30 percent reduction in after-tax income in the late 1990s (based on the underlying data in Figure 4), but we also find a 15 percent *increase* in after-tax income at the 2nd percentile when comparing the 1997–2000 and 2001–2004 periods. In Figure 4 we observe no discernable long-term downward trend in income at the low end of the distribution. For example, the average income level at the 2nd percentile is \$533 from 1979–1994 and it is a slightly higher \$545 from 1995–2005. This suggests that relative to the issue of top coding discussed above, transfer income underreporting is not likely to impart significant

[9] Though Bollinger (1998), using data in the CPS matched to Social Security records, shows that if anything the poor *overstate* earnings in the CPS relative to administrative Social Security data.

bias in our measures of inequality in the 1990s. At the same time Figure 4 does reveal evidence of a strong upward trend in income beginning in the mid 1990s in the upper half of the distribution. It appears that among single mother families rising inequality in the 1990s is an phenomenon heavily concentrated in the upper tail of the income distribution similar to the trend in the general population (Piketty and Saez 2003; Autor, et al. 2005).

A. Within versus Between Group Inequality

Table 1 showed that the demographic composition of single mothers changed dramatically over the past several decades, and with the documented rise in inequality in Figure 2 for all single mothers pooled together, in this section we explore whether and to what extent rising inequality cut across various demographic groups of lone mothers and the roles of within and between group inequality. Table 2 presents trends in I_2 and the relative mean income of the groups defined in equation (3). Across all major subgroups, nonworking single mothers had the largest trend increase in inequality, and a concomitant large reduction in relative mean income. This highlights growing instability among single mothers disconnected from the workforce (Blank 2007). Other groups experiencing large increases in inequality include mothers who are never married or separated, or who are white or other race. However, as reflected in equation (3) whether inequality is due to inequality within groups or between groups depends on the interaction of group-specific inequality, population share, and relative mean income.

Table 3 presents the average contributions of within and between-group inequality based on education attainment, age, marital status, race, and employment status across the 1979-2005 period. For each panel in the table we depict the average of the 27 annual estimates of within- and between-group inequality, and also show the contribution of each sub-group to within inequality (e.g. the four estimates for within education group add up to the total

(0.178=0.023+0.059+0.052+0.044)). Table 3 reveals that most of the inequality in a typical year is accounted for by inequality within groups and not between groups. For example, inequality within education groups accounts for 82 percent of the total, with more than high school educated mothers being the largest contributor to within education group inequality. Likewise, within employment status group inequality accounted for 87 percent of the total, and although inequality within the group of non-workers increased more than any other group as shown in Table 2, the declining population shares and relative incomes of non-workers fell more and thus reduced non-workers contribution to overall inequality in Table 3. The other panels in the table suggest a similar story in that nearly all of the inequality in a given year is due to within-group inequality and very little is attributed to between group differences. Within-group inequality among single mother families is most prominently affected by those with more than a high school education, those age 31 and older, those widowed or divorced, and those who are white.

In Table 4 we record the results of the demographic change decompositions of equation (4) across the entire sample period of 1979 to 2005 as well as across five-year intervals (we include the extra period in the first change of 1979 to 1985). To facilitate comparisons across the multiple changes, we divide both sides of equation (4) by the base year inequality $I_2(1979)$ and report the results as percentage changes.[10] The bulk of the 27.5 percent rise in inequality is attributed to a rise in within-group inequality regardless of the group selected to conduct the decomposition. However, this is often because of large but offsetting changes in the two terms affecting between-group inequality. For example, there was a large and disequalizing increase in the share of single moms with college degrees (or at least some college) between 1979 and 2005—the “Murphy Brown” effect. However this higher educated mother with some college

[10] In some cases rounding error after the calculations may result in some rows not adding up.

placed lower on average in the 2005 distribution of income than she would have in 1979, and thus there was an equalizing reduction in relative mean incomes that offset the pure population share effect (see Table 2). A similar scenario unfolded based on employment status of single mothers as well as past marital status. In the 1990s there was a substantial increase in the contribution of employment to inequality, but some of these new workers were placed in the lower end of the distribution and thus reducing the relative mean income of workers, which equalized incomes in the overall population of single mothers. In the case of marital status, there was an equalizing shift in the population toward never-married mothers, but their relative mean incomes fell slightly compared to widowed, separated, and divorced mothers. Examining the inequality changes across sub-periods reveals a similar trend in favor of within-group changes being the prominent factor in changes in inequality. Again this is generally achieved because of substantial offsetting changes in relative population shares and relative mean incomes. This suggests that the time-series of cross-sectional decompositions of within- and between-group inequality in Table 3 understates the role of important between group changes in inequality over the past two decades arising from large shifts in education attainment, age, previous marital status, and employment status.

The basic trends are confirmed in the shift-share analysis in Table 5. Here we conduct the counterfactual experiments of predicting inequality in 1979 using equation (3) and assuming that population shares, relative mean incomes, and group-specific inequalities alternatively take on their respective 2005 values while holding the other terms fixed at the 1979 values. For example, in 1979 our estimate of I_2 is 0.179, but if the population shares of single mothers across education groups in 1979 were instead given their 2005 values then inequality would have been more than double (0.352). Likewise, holding all else equal, if we replace the 1979 relative mean incomes with their 2005 values then inequality would have been near zero (0.015); and if we instead replaced the group-specific inequalities with the 2005 values then inequality is predicted to be 0.23. The numbers in parentheses reflect the percentage of the actual change that is captured by the predicted change in inequality (Jenkins 1995). Specifically, let $\widehat{I_2}(2005)$ be the predicted inequality when replacing the 1979 values with their 2005 counterparts; then the numbers in parentheses are $100\% * \left(\frac{\widehat{I_2}(2005)-I_2(1979)}{I_2(2005)-I_2(1979)}\right)$. Consistent with the robust decompositions in Table 4, in Table 5 there is evidence of substantial between group changes across education level, marital status, and employment status, but the shifts in population shares are counteracted by shifts in relative mean incomes that are similar in magnitude but opposite in direction, leaving the bulk of the change in inequality accounted for by within group changes (the last column in Table 5).

B. Factor Decomposition of Inequality

How the demographic changes implicitly translate into the income factors underlying inequality is depicted in Figure 5, which shows trends in the cross sectional decomposition of disposable income-to- needs inequality into its factor shares based on equation (6).[11] Both earnings and other nonlabor income lie above the x-axis because they are 'disequalizing' and contribute to inequality, while transfers and taxes each lie below the x-axis as they are 'equalizing' factors in the distribution of income. Figure 5 shows that the bulk of after-tax income to needs inequality in any given year emanates from earnings inequality in the labor market. The major equalizer is the tax system, both through the refundable EITC and progressive marginal tax rates—in a typical year the tax system reduced earnings inequality by

[11] As with total income, we conduct our decomposition of factor shares based on residual earnings, transfers, other nonlabor income, and taxes from a regression of each factor on a quartic in age. All income factors are adjusted by needs prior to estimation.

about one-third. Perhaps surprising, income transfers have never played a significant role in reducing inequality among single mothers, averaging about 8 percent prior to the welfare reforms of the mid 1990s, and about 4 percent after welfare reform. While this is a 50 percent reduction it had little impact on overall inequality. We do note, though, that as shown in Table 2 non-employed single mothers had the largest growth in inequality over the past decade, which could in part be due to the loss of transfer income.

In Table 6 we present the results of the factor-specific changes in inequality from equation (7) across the entire sample period of 1979 to 2005 as well as across five-year intervals (again, we include the extra period in the first change of 1979 to 1985). As in Table 4, we divide both sides of equation (7) by the base year inequality $I_2(1979)$ and report the results as percentage changes. In the first row of Table 6 we see that changes in earnings inequality drove the nearly 30 percent increase in total income inequality over the past two and a half decades, and in the absence of the U.S. tax system inequality would have been almost 5 percentage points higher. Income transfers have a negligible effect on changes in inequality, and if anything are on net disequalizing, reflecting the large reductions in program participation. The five-year inequality change decompositions show considerable within-period variation in the relative roles of earnings, transfers, other income, and taxes on inequality. In most subperiods inequality would be significantly higher in the absence of income taxes, though there are some exceptions in the periods surrounding the Tax Reform Act of 1986 and the 2001 and 2003 tax cuts.

The results in Figure 5 and Table 6 make transparent that the rising income inequality among single mothers is driven by rising earnings inequality. With the influx of large numbers of mothers into the labor force in the 1990s the higher earnings inequality may be due to a compositional change of the workforce (Lemieux 2006), or it may simply reflect increased earnings dispersion of workers. That is, the variance of earnings depends on the relative role of changes in the extensive margin of entry into employment and the intensive margin of earnings conditional on being a worker. To see this possible interaction between the extensive and intensive margins in the Appendix we show that the unconditional variance of earnings can be written as

(8) $V(W) = E\{W|P = 1\}^2 * \Pr(P = 1) * (1 - \Pr(P = 1)) + V(W|P = 1) * \Pr(P = 1)$,

where W is earnings, P is an indicator variable equal to one if a single mother participates in the labor force, and E is the expectations operator. The unconditional variance of earnings in equation (8) contains two terms—the square of the conditional mean of earnings weighted by the variance of the extensive employment margin (the probability of working times one minus that probability), and the conditional variance of earnings among workers weighted by the probability of working. Thus, the variance of earnings depends on whether the employment rate, the conditional mean, and the conditional variance are rising, falling, or remaining the same. For example, suppose that the mean and variance of earnings conditional on working are held constant but the probability of working rises. If we assume that $\Pr(P = 1) > \frac{1}{2}$, then the first term in equation (8) is falling, while the second term is rising. In fact, however, as discussed previously both the conditional mean of earnings and the employment rate have been rising so it is less clear cut a priori which of the two terms in equation (8) dominates.

In Figure 6 we present the decomposition of the unconditional earnings to needs variance in equation (8) with the first term of the squared conditional mean represented on the left axis, and both the conditional variance and total unconditional variance represented on the right axis. The figure reveals that the unconditional variance has been increasing over the past two decades, especially in the 1990s when it increased 50 percent between 1992 and 2005. This increased earnings variance is largely driven by increases in the conditional variance of earnings. Notice with the surge of single mothers into the labor force in the 1990s the squared conditional mean weighted by the variance of the extensive employment margin (the first term in equation (8)) was falling, and the conditional variance rose in response as predicted. In the 2000s with the onset of the recession the employment rate of single mothers fell slightly, and both the conditional mean and conditional variance of earnings leveled off. Although rising participation alone could cause the earnings variance to increase, the story here is more complicated. The percentiles presented in Figure 4 showed growing inequality in the upper half of the income distribution. This suggests that high skilled single mothers in the labor force likely benefited from the rising premium to skill documented extensively in the literature, which would increase the variance of earnings over and above the participation effect (Autor, et al. 2005; Lemieux 2006).

A related issue is whether the higher earnings variance is driven by changes in the variance of hourly wages or hours of work. In Figure 7 we depict trends in the variance of average real hourly wages (deflated by the personal consumption deflator, not by needs thresholds) on the left axis and variance of annual hours of work on the right axis.[12] Figure 7 makes clear that the rising earnings variance for single mothers has been led by an increased variance of average hourly wages since the mid 1990s. The variability of work hours actually fell in the 1990s, which reflects in part the increase in full time working mothers. That increasing earnings dispersion is caused by rising wage dispersion is consistent with the results from the literature on men, the difference being that it took more than a decade longer for this trend to affect single mothers.

[12] For Figure 7 we restrict the sample to those mothers with average hourly earnings between $2 and $250. The results were unduly influenced by some extreme outliers on each end of the distribution, and thus we trimmed the data for ease of presentation.

V. Conclusion

Over the past two and a half decades the demographic composition of single mothers has changed dramatically to an older, more educated population, and the attendant composition of their incomes has changed in kind. We examined whether and to what extent this shift of single mothers to more closely resemble the fictional television character Murphy Brown translated into changes in income inequality among single mothers. Our results suggested that disposable income-to-needs inequality increased about 30 percent among single mothers in the United States from 1979 to 2005. Further analysis indicated that most of the increase was manifested in the form of higher within-group inequality rather than across demographic groups of mothers. However, the role of between-group inequality was attenuated because of offsetting changes in relative population shares and mean incomes across groups. In terms of income components, the rise in income inequality was prominently a result of higher earnings inequality.

After-tax incomes of single mothers rose significantly between the mid 1990s and mid 2000s, ranging from 20 percent growth at the 25th percentile to nearly 40 percent growth at the 99th percentile. However, the rise in the cross-sectional variance swamps the increase in income levels, which fueled the rise in inequality identified by the squared coefficient of variation. The influx of single mothers into the labor force in the 1990s led to a rise in the conditional variance of earnings, which likely reflected both the placement of these new workers at a lower point of the income distribution as well as the rising premium to skill offered to those working women with comparatively high skills. Indeed, much of the increase in income inequality comes from the upper half of the income distribution. The combination of changing demographic composition with rising upper tail inequality corroborates recent work on the wage inequality of male and female workers both by Lemieux (2006), who emphasized demographic change, and

Autor, et al. (2005), who emphasized upper-tail changes in the wage distribution. Another result that corroborates the earlier research is that the increased earnings variance in the 1990s was driven by a higher variance of hourly wages rather than hours of work. In short, the "Murphy Brown" effect on the composition of single mothers in recent years suggests that the general forces that will determine future changes in inequality of men and women are likely to translate into similar changes in income inequality among single mothers.

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Appendix

In this appendix we provide a brief derivation of equation (8) in the text. To begin, the unconditional variance of earnings, W, can be written as

(A.1) $V(W) = V(E\{W|P\}) + E\{V(W|P)\}$,

which is the sum of the variance of the conditional mean of earnings and the expected conditional variance (where E is the expectations operator). The first term in equation (A.1) is the variance of the conditional mean of earnings, and noting that $E\{W|P = 0\} = 0$ we can write the first term as

(A.2) $V(E\{W|P\}) = (E\{W|P = 1\} - E\{W\})^2 * \Pr(P = 1) + E\{W\}^2 * \Pr(P = 0)$.

Since $E\{W\} = E\{W|P = 1\} * \Pr(P = 1) + E\{W|P = 0\} * \Pr(P = 0) = E\{W|P = 1\} * \Pr(P = 1)$, the first and second terms in (A.2) simplify and combine to become $E\{W|P = 1\}^2 * \Pr(P = 1) * (1 - \Pr(P = 1))$.

Likewise, noting that $V(W|P = 0) = 0$ we can write the second term in equation (A.1) as

(A.3) $E\{V(W|P)\} = V(W|P = 1) * \Pr(P = 1)$,

and substituting (A.2) and (A.3) into (A.1) yields equation (8) of the text.

Figure 1: Trends in the Mean and Variance of After-Tax Income to Needs

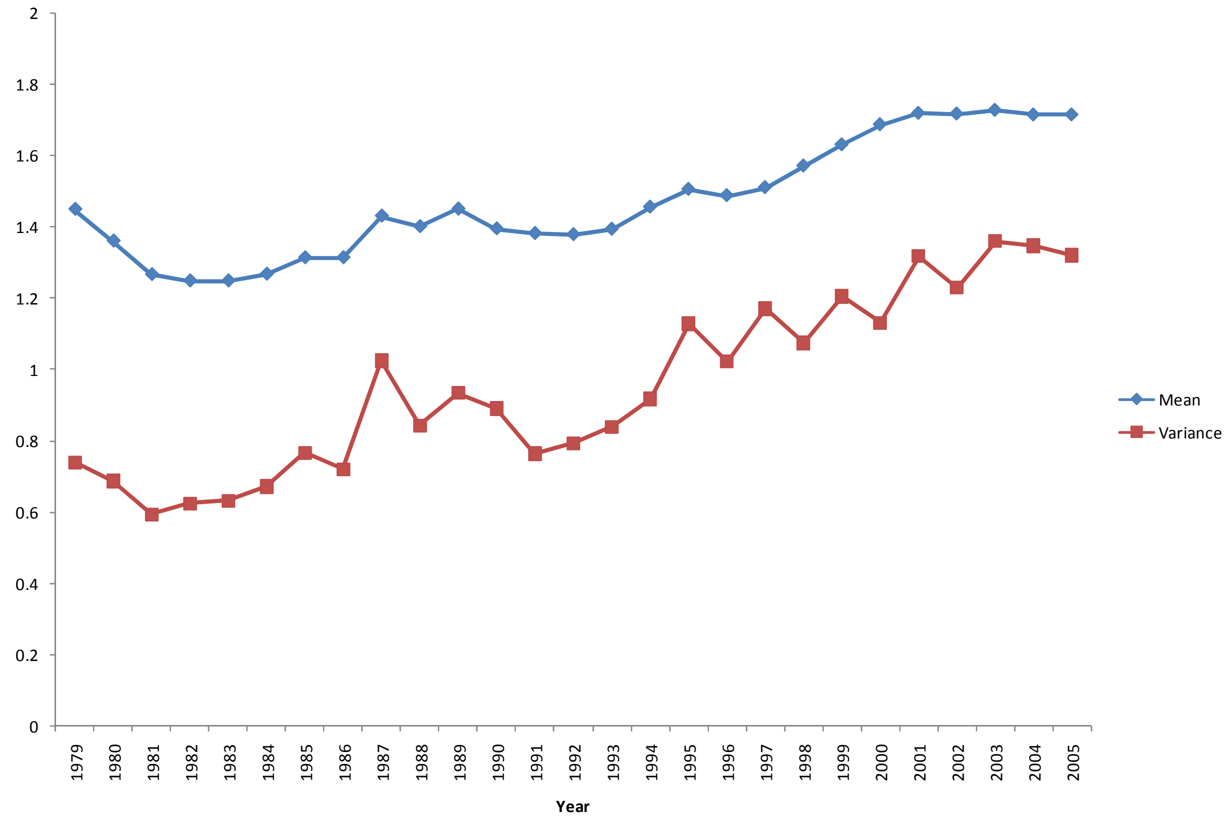
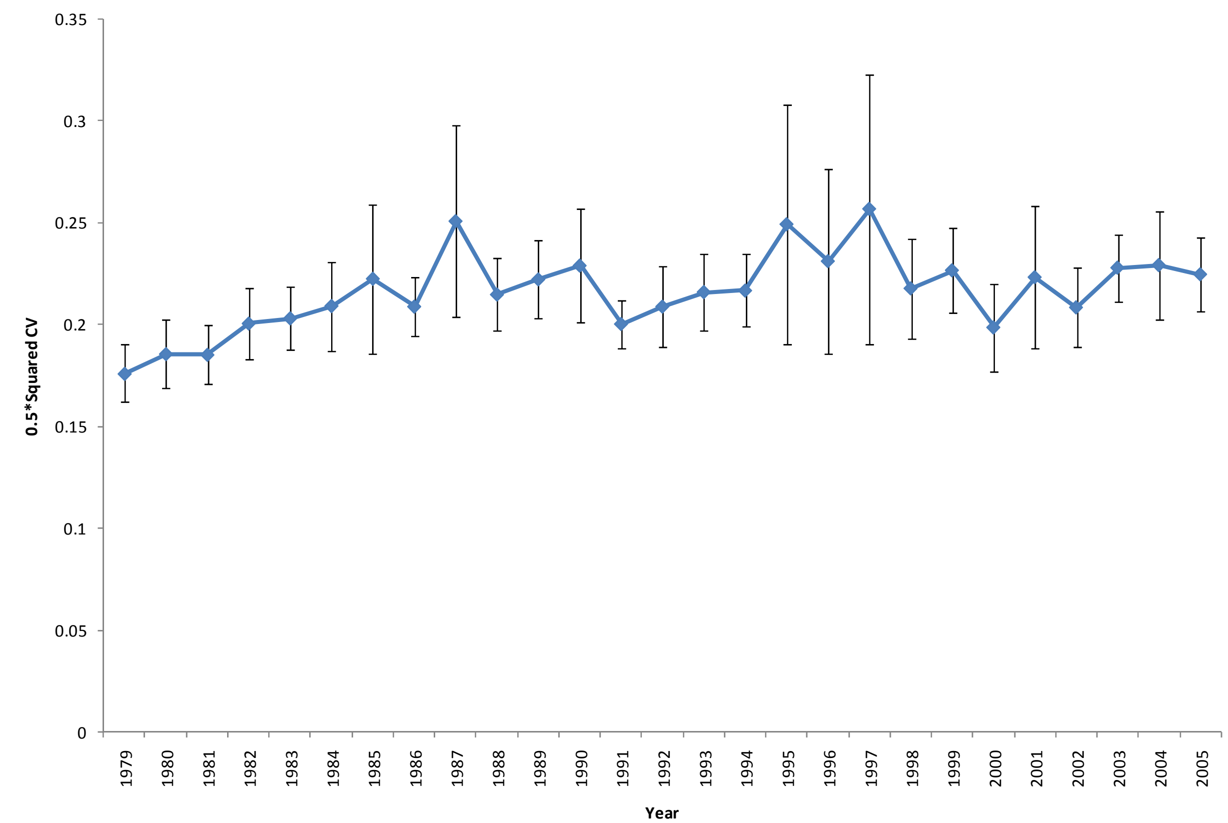


Figure 2: Trends in After-Tax Income to Needs Inequality



Note: The bars refer to 95 percent bootstrap confidence intervals based on 100 bootstrap replications.

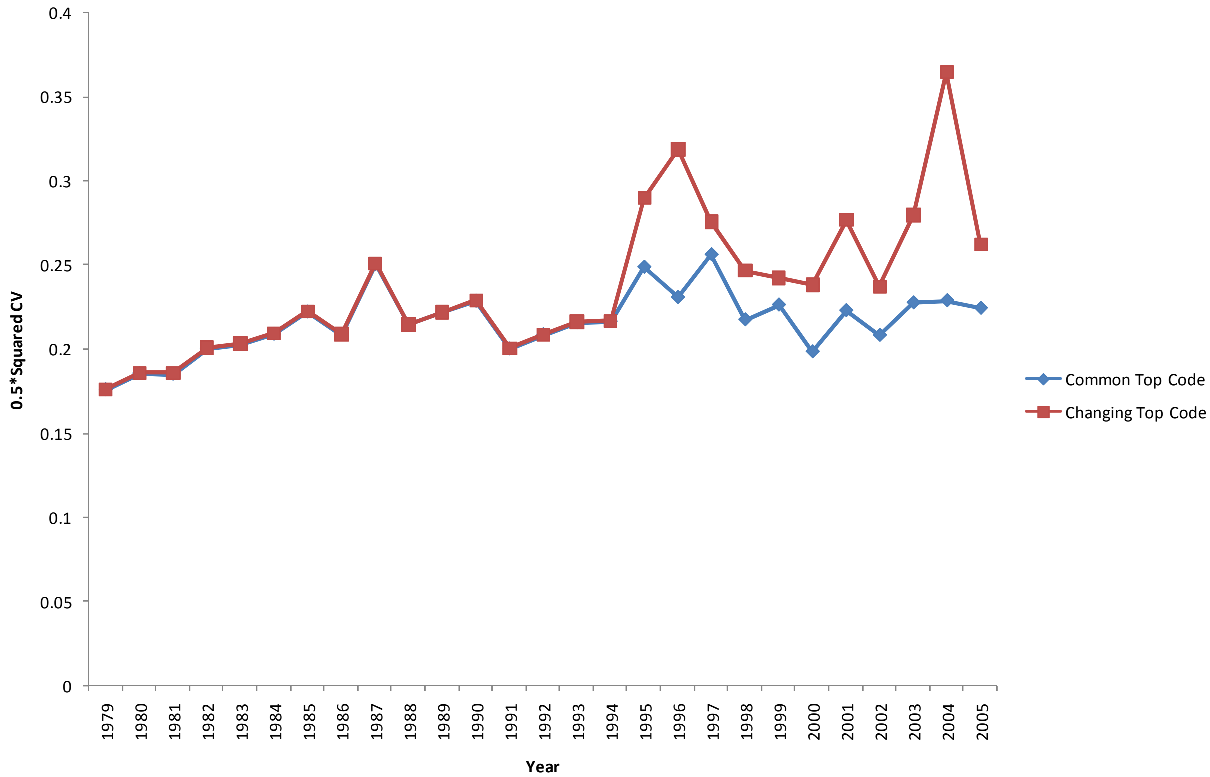


Figure 3: The Role of Top Coding on Trends in After-Tax Income to Needs Inequality

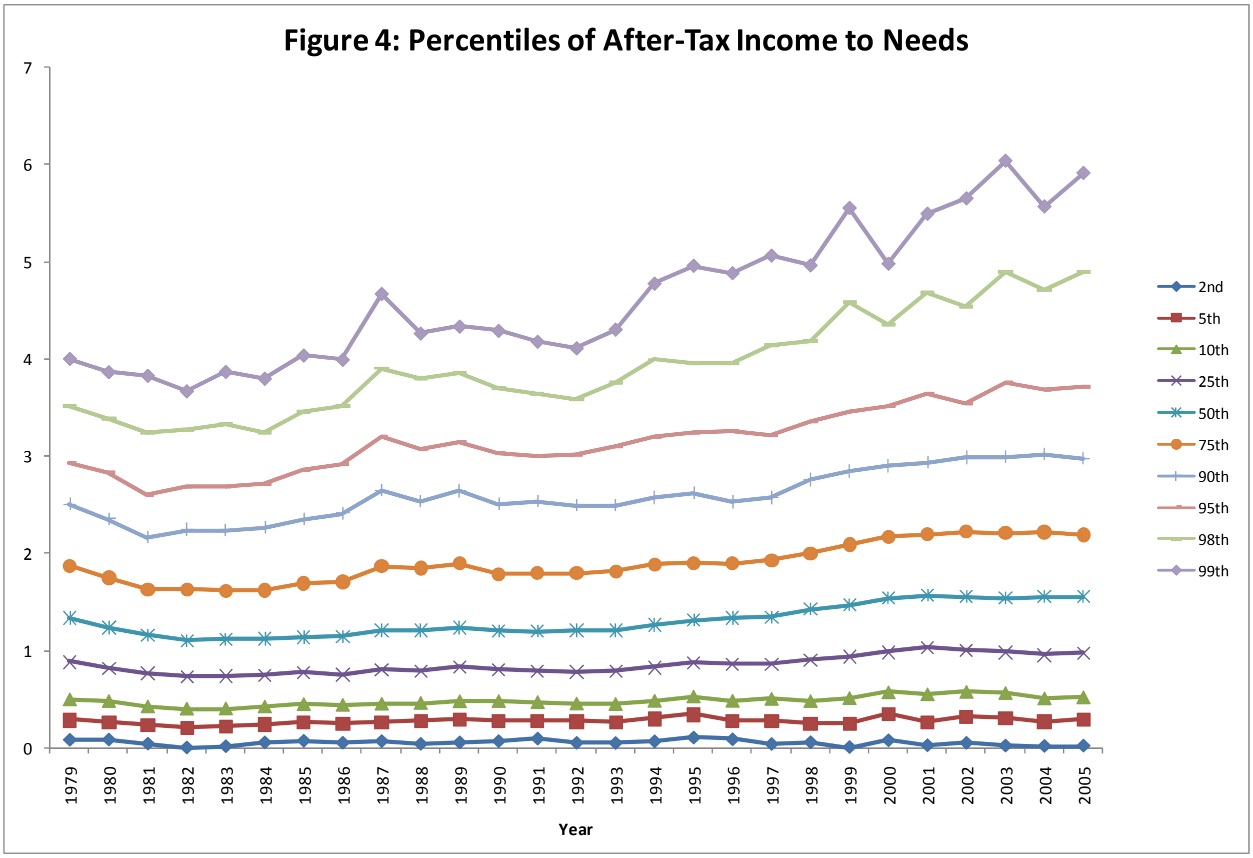


Figure 4: Percentiles of After-Tax Income to Needs
7
6
5
4
3
2
1
0
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
Year
2nd
5th
10th
25th
50th
75th
90th
95th
98th
99th

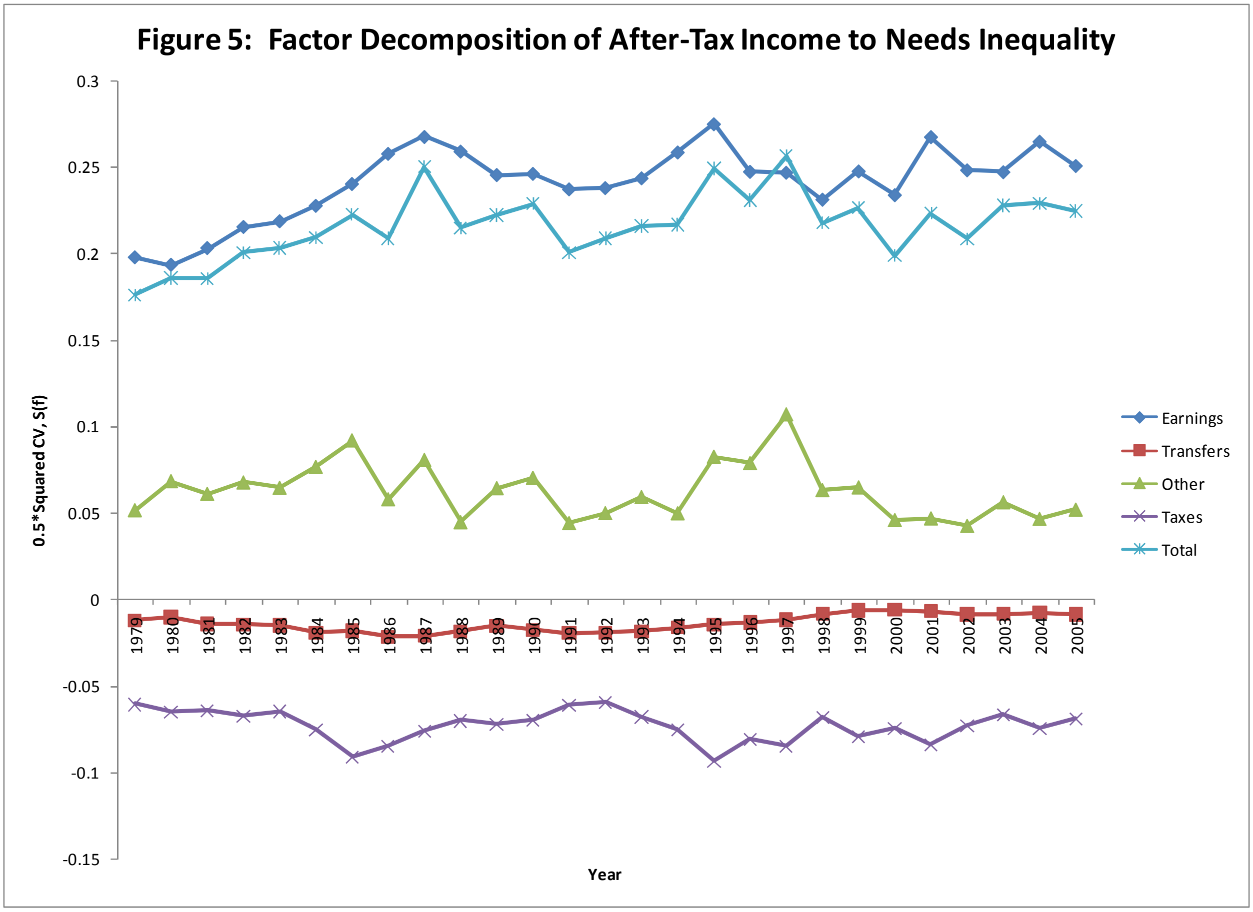


Figure 5: Factor Decomposition of After-Tax Income to Needs Inequality
0.5*Squared CV, S(f)
Year
Earnings
Transfers
Other
Taxes
Total
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
1979
1980
1981
1982
1983
1984
1985
1986
1987
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1989
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2004
2005

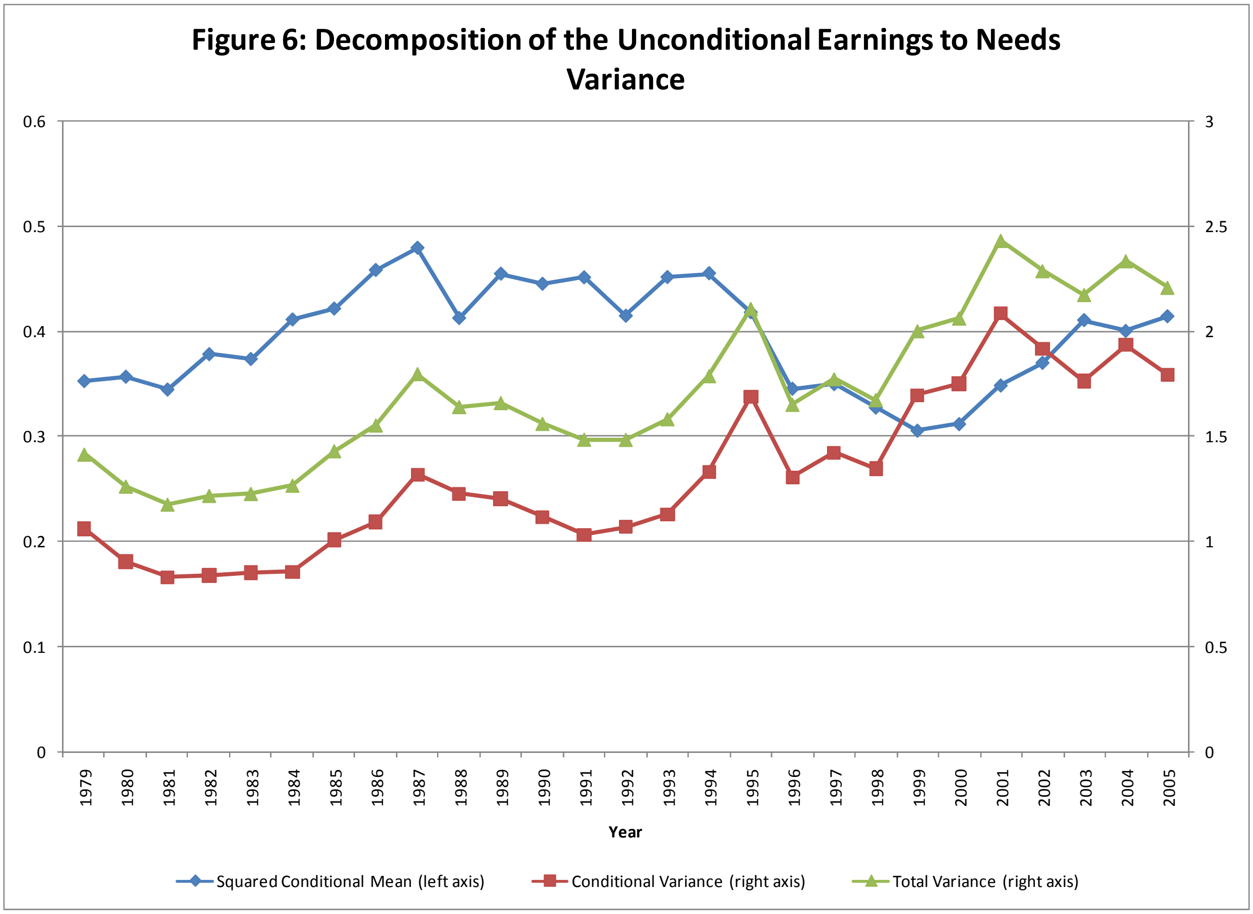
Figure 6: Decomposition of the Unconditional Earnings to Needs Variance
0.6
0.5
0.4
0.3
0.2
0.1
0
3
2.5
2
1.5
1
0.5
0
1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005
Year
Squared Conditional Mean (left axis)
Conditional Variance (right axis)
Total Variance (right axis)

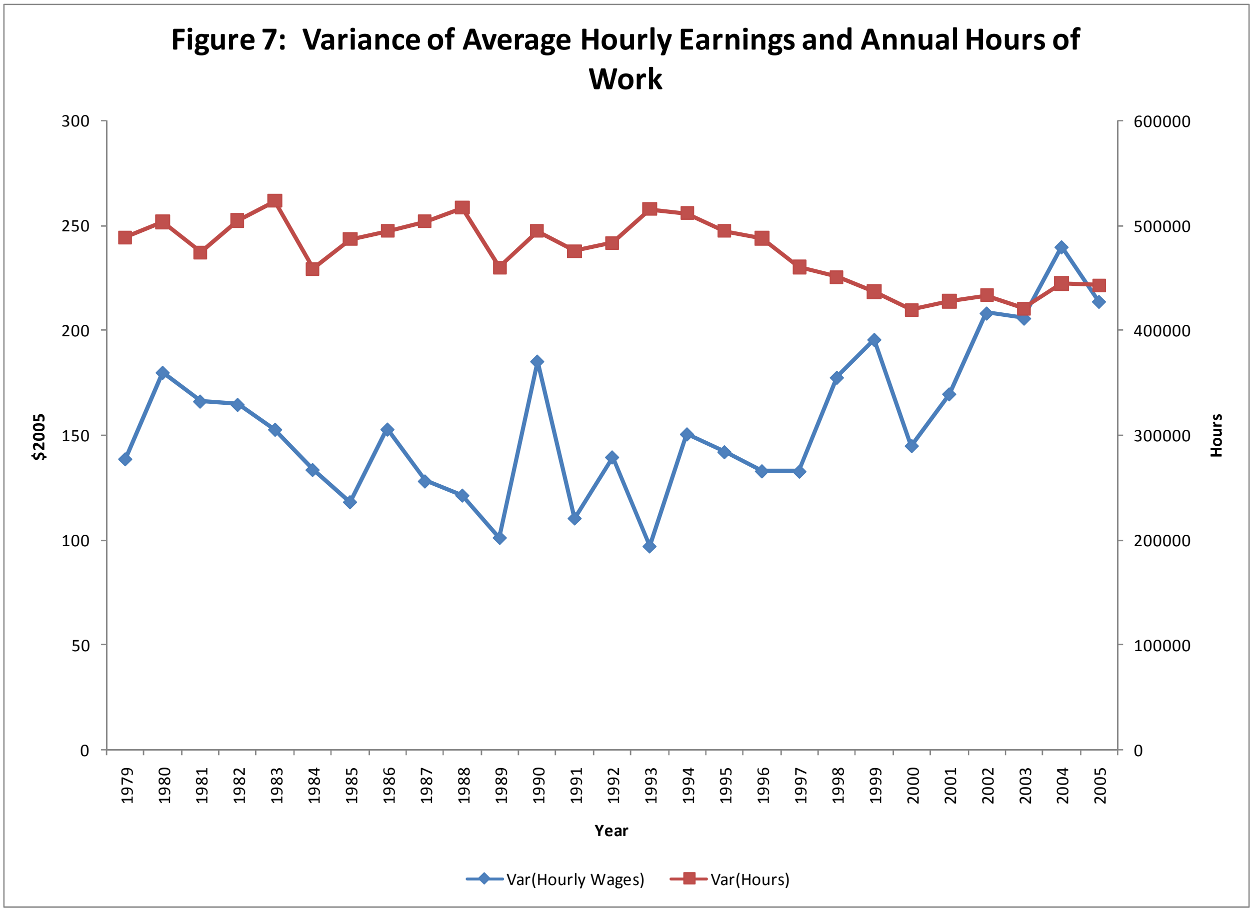

Figure 7: Variance of Average Hourly Earnings and Annual Hours of Work
$2005
Hours
Year
Var(Hourly Wages)
Var(Hours)
0
50
100
150
200
250
300
0
100000
200000
300000
400000
500000
600000
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005

Table 1: Trends in Population Shares for Selected Groups of Single Mothers

	1979	1985	1990	1995	2000	2005
Education Level						
Less than 12	0.371	0.300	0.276	0.231	0.180	0.169
High School	0.413	0.433	0.436	0.342	0.349	0.337
Between 12 & 16	0.147	0.183	0.190	0.318	0.342	0.352
At least 16	0.069	0.084	0.098	0.109	0.129	0.142
Age						
Under age 30	0.374	0.362	0.343	0.316	0.318	0.298
Age 31-40	0.390	0.435	0.441	0.430	0.391	0.377
Over age 40	0.236	0.203	0.216	0.254	0.291	0.325
Marital Status						
Separated	0.243	0.222	0.212	0.196	0.142	0.132
Widowed/divorced	0.577	0.523	0.480	0.460	0.455	0.436
Never married	0.180	0.255	0.308	0.344	0.403	0.431
Race						
White	0.692	0.695	0.681	0.700	0.699	0.683
Black	0.279	0.279	0.280	0.258	0.256	0.250
Other race	0.028	0.027	0.039	0.042	0.045	0.067
Employment Status						
Worker	0.767	0.710	0.727	0.774	0.875	0.836
Non-worker	0.233	0.290	0.273	0.226	0.125	0.164

Table 2: Trends in Inequality and Relative Means for Selected Groups

		1979	1985	1990	1995	2000	2005
Less than 12	$0.5*CV^2$	0.159	0.295	0.186	0.351	0.298	0.211
	Relative Mean	0.747	0.680	0.679	0.676	0.663	0.651
High School	$0.5*CV^2$	0.137	0.157	0.209	0.171	0.171	0.177
	Relative Mean	1.060	0.993	0.990	0.923	0.899	0.844
Between 12 & 16	$0.5*CV^2$	0.151	0.148	0.143	0.198	0.136	0.156
	Relative Mean	1.212	1.217	1.153	1.110	1.072	1.057
At least 16	$0.5*CV^2$	0.125	0.138	0.159	0.174	0.131	0.160
	Relative Mean	1.544	1.702	1.653	1.610	1.551	1.643
Under age 30	$0.5*CV^2$	0.092	0.140	0.137	0.100	0.127	0.109
	Relative Mean	1.061	1.003	0.992	0.975	1.010	0.978
Age 31-40	$0.5*CV^2$	0.167	0.216	0.242	0.313	0.199	0.206
	Relative Mean	1.001	1.048	1.028	1.008	0.986	0.973
Over age 40	$0.5*CV^2$	0.365	0.412	0.351	0.311	0.276	0.332
	Relative Mean	0.901	0.891	0.956	1.018	1.007	1.052
Separated	$0.5*CV^2$	0.169	0.286	0.262	0.432	0.217	0.264
	Relative Mean	0.804	0.834	0.851	0.859	0.870	0.863
Widowed/divorced	$0.5*CV^2$	0.174	0.199	0.229	0.219	0.217	0.235
	Relative Mean	1.106	1.117	1.138	1.136	1.112	1.136
Never married	$0.5*CV^2$	0.115	0.195	0.152	0.174	0.140	0.167
	Relative Mean	0.925	0.905	0.887	0.899	0.920	0.905
White	$0.5*CV^2$	0.168	0.205	0.226	0.257	0.195	0.232
	Relative Mean	1.086	1.071	1.071	1.059	1.053	1.044
Black	$0.5*CV^2$	0.154	0.254	0.195	0.196	0.187	0.186
	Relative Mean	0.806	0.825	0.839	0.852	0.883	0.900
Other race	$0.5*CV^2$	0.150	0.195	0.254	0.177	0.207	0.213
	Relative Mean	0.799	0.990	0.912	0.932	0.847	0.927
Worker	$0.5*CV^2$	0.148	0.187	0.176	0.210	0.164	0.173
	Relative Mean	1.114	1.145	1.146	1.131	1.083	1.113
Non-worker	$0.5*CV^2$	0.150	0.188	0.313	0.169	0.298	0.423
	Relative Mean	0.626	0.644	0.610	0.551	0.420	0.422

Table 3: Between Group and Within Group After-Tax Income-to-Needs Inequality

	Overall	Between	Within
Education	0.216	0.038	0.178
< 12			0.023
12			0.059
> 12 & < 16			0.052
> = 16			0.044
Age	0.216	0.001	0.215
< 30			0.037
31-40			0.093
> 40			0.085
Marital Status	0.216	0.007	0.209
Separated			0.035
Widowed/Divorced			0.133
Never Married			0.041
Race	0.216	0.005	0.212
White			0.166
Black			0.038
Other			0.008
Employment Status	0.216	0.028	0.188
Worker			0.171
Non-Worker			0.017

Note: The numbers in the table are averages across the 27 annual estimates of within and between group inequality.

Table 4: Decomposition of Percentage Changes in Income-to-Needs Inequality by Subgroups

	Education Level			
	Percent Change in I_2	Changes in within-group inequality	Changes in population shares	Changes in relative mean income
Total Period				
1979-2005	27.50	20.50	103.50	-96.40
Five-Year Change				
1979-1985	26.28	22.10	28.00	-23.70
1985-1990	3.80	6.10	14.40	-16.80
1990-1995	11.40	13.10	32.70	-34.30
1995-2000	-28.70	-23.90	19.50	-24.30
2000-2005	14.80	6.60	11.80	-3.90
	Age			
	Percent Change in I_2	Changes in within-group inequality	Changes in population shares	Changes in relative mean income
Total Period				
1979-2005	27.50	9.10	16.40	2.10
Five-Year Change				
1979-1985	26.28	27.40	2.20	-3.20
1985-1990	3.80	0.90	1.70	1.10
1990-1995	11.40	7.30	4.30	-0.10
1995-2000	-28.70	-28.90	2.30	-1.90
2000-2005	14.80	7.50	5.80	1.40
	Marital Status			
	Percent Change in I_2	Changes in within-group inequality	Changes in population shares	Changes in relative mean income
Total Period				
1979-2005	27.50	37.30	-33.50	23.90
Five-Year Change				
1979-1985	26.28	27.20	-9.00	8.10
1985-1990	3.80	4.10	-10.60	10.10
1990-1995	11.40	14.30	-5.80	3.00
1995-2000	-28.70	-23.80	-1.00	-3.90
2000-2005	14.80	13.80	-4.50	5.40

Table 4 continued: Decomposition of Percentage Changes in Income-to-Needs Inequality by Subgroups

	Race			
	Percent Change in I_2	Changes in within-group inequality	Changes in population shares	Changes in relative mean income
Total Period				
1979-2005	27.50	33.80	0.00	-6.20
Five-Year Change				
1979-1985	26.28	28.00	0.20	-2.00
1985-1990	3.80	4.10	-1.80	1.30
1990-1995	11.40	12.40	3.90	-4.90
1995-2000	-28.70	-27.80	-0.20	-0.60
2000-2005	14.80	16.00	-1.50	0.20
	Employment Status			
	Percent Change in I_2	Changes in within-group inequality	Changes in population shares	Changes in relative mean income
Total Period				
1979-2005	27.50	27.70	26.30	-26.40
Five-Year Change				
1979-1985	26.28	22.80	-19.90	23.50
1985-1990	3.80	3.10	5.80	-5.30
1990-1995	11.40	9.90	18.70	-17.20
1995-2000	-28.70	-20.90	36.50	-44.10
2000-2005	14.80	7.10	-14.80	22.40

Note: The decompositions as calculated add up exactly, but some rows may not because of rounding error in converting to percentages.

Table 5: Shift-Share Analysis of After-Tax Income-to-Needs Inequality

	2005 Population Share	2005 Relative Mean	2005 Group-Specific Inequality
		1979 Inequality = 0.176	2005 Inequality = 0.224
	Predicted 1979 Inequality if Change to		
Education	0.352	0.015	0.23
	(362)	(-331)	(111)
Age	0.179	0.184	0.191
	(7)	(16)	(30)
Marital Status	0.144	0.214	0.241
	(-65)	(77)	(133)
Race	0.172	0.167	0.229
	(-8)	(-18)	(109)
Employment Status	0.214	0.143	0.236
	(78)	(-68)	(124)

Note: The shift share analysis is based on equation (3) and holds other factors constant at their 1979 values and replaces successively each of the three components with their respective 2005 values. The number in parentheses is the percentage of the ratio of the difference between the predicted inequality and the actual 1979 inequality over the difference between the actual 2005 and 1979 inequality values.

Table 6: Decomposition of Percentage Changes in Income-to-Needs Inequality by Income Source

	Percent Change in I_2	Contribution of earnings	Contribution of transfers	Contribution of other income	Contribution of taxes
Total Period					
1979-2005	27.50	30.20	1.90	0.20	-4.80
Five-Year Change					
1979-1985	26.28	24.10	-3.40	22.80	-17.22
1985-1990	3.80	3.40	0.40	-12.20	12.20
1990-1995	11.40	16.40	1.70	6.90	-13.60
1995-2000	-28.70	-23.50	4.70	-20.70	10.80
2000-2005	14.80	9.70	-1.40	3.40	3.10

Note: The decompositions as calculated add up exactly, but some rows may not because of rounding error in converting to percentages.

Appendix Table 1: Summary Statistics

	Mean	Standard Deviation
After-Tax Income	23030	16168
After-Tax Income to Needs	1.49	1.06
Earnings	18174	20725
Transfers	4195	5933
Other Nonlabor Income	3184	8031
Taxes	2523	6632
Less than High School	0.25	0.43
High School or Equivalent	0.38	0.49
Some College	0.26	0.44
At least 16 years	0.11	0.31
Age	34.70	8.14
Race is White	0.69	0.46
Race is Black	0.27	0.44
Other Race	0.04	0.21
Separated	0.19	0.39
Widowed/Divorced	0.49	0.50
Never Married	0.33	0.47
Observations	99,436	