

Effects of Taxes and other Government Policies on Income Distribution and Welfare

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Abstract

Marginal tax rates have larger income redistribution and equilibrating welfare effects than do social insurance or direct transfer programs. The Earned Income Tax Credit has smaller but still statistically significant desirable effects. Social insurance programs have little effect except for Supplemental Security Income, which increases equality. The minimum wage and transfer programs (AFDC/TANF and food stamps) either have no statistically significant effect or negative distributional impacts. These effects are qualitatively the same regardless of the inequality measure used: Gini, standard deviation of logarithms, relative mean deviation, coefficient of variation, and various Atkinson indexes.

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Do federal and state taxes, minimum wage laws, social insurance policies, and transfer programs make the income distribution more equal? Asking this question may appear pointless because the answer may vary with the measure of equity used. However, we show that all the well-known equity measures give the same qualitative answer.¹ Using data from the 50 states from 1981 to 1997, we show that marginal income tax rates and the Earned Income Tax Credit play a more important role in equalizing income than do the other government programs. Indeed, we find that several of these other programs have undesirable distributional effects.

We examine the distributional effects of major government tax and welfare policies using all the common, traditional inequality measures: the Gini index, coefficient of variation of income, relative mean deviation of income, and standard deviation of the logarithm of income, as well as the Atkinson welfare index. In addition to examining the effect of these government policy variables, we examine how changes in macro conditions and demographic variables over time and across the 50 states affect income inequality. Most previous studies have examined the effect of only a single policy, ignoring the influences of other government policies, market conditions, and demographics. As Freeman (1996) observes, “Because the benefits and costs of the minimum (wage)/other redistributive policies depend on the conditions of the labor market

¹ Dalton (1920) suggested that all common welfare measures would give the same rankings (level) across countries “in most practical cases.” However, Atkinson (1970) demonstrated that they give different rankings. Our claim is different. We show that changes in government policies (and macroeconomic and aggregate demographic variables) change the rankings of almost all measures in the same direction as a practical matter.

and the operation of the social welfare system, the same assessment calculus can yield different results in different settings.” Moreover, rather than focus on only the effects on low-paid workers as do several of these studies, we examine the policy effects on the entire income distribution.

After briefly surveying the literature, we review the major inequality measures. Then we use standard parametric models to examine how policies, macro conditions, and demographics affect each of the inequality measures. We examine the robustness of our results to various estimation technique and alternative specifications. Finally, we determine the dollar-denominate welfare magnitude of the various policies.

The Literature

Mitrusi and Poterba (2000) describe the change in tax policies and Meyer and Rosenbaum (2000) outline changes in major government anti-poverty policies during our sample period, 1981 to 1997. Typically tax studies (such as Feldstein 1995 and Feenberg and Poterba 2000) focus on the effect of taxes on the high end of the income distribution.

Most older income inequality studies (e.g., Thurow 1970) emphasized the impacts of macroeconomic conditions. More recent studies (see Bishop, et al. 1994, for a survey of this literature) also examined the effects of changes in demographic characteristics, labor market conditions, and some policies.

In addition, there is a huge literature on government anti-poverty polices that focuses on the behavior effects of these polices, such as on labor supply, participation, turn over, and family structure (see the overview by Moffitt 1992). Treating policy changes as exogenous, the labor literature uses variations in policy parameters (intertemporal, spatial, or across different demographic groups) as the sources of identification for their policy evaluation. For example,

Card and Kruger (1994, 1995, 2000), DiNardo et al. (1996), Lee (1999), Neumark and Wascher (1992, 2000), Neumark et al. (1998) investigate in great details the impacts of change in minimum wage laws on various aspects of individual labor market behaviors and its distributional implications. Eissa and Hoynes (1998), Eissa and Liebman (1996) and Neumark and Wascher (2001) study the Earned Income Tax Credit's impact on labor market participation of single mothers, wives, and its distributional impacts on the low income families.

However, few existing studies of anti-poverty policies explicitly considered their welfare effects. Moreover, most papers on the effect of programs on income distribution examined only one program and focused on the low end of the income distribution. No previous study has examined the distribution interaction effects of all the major government anti-poverty policies on the entire income distribution.

Measure of Inequality

We employ four commonly used traditional inequality measures as well as the Atkinson index. All of our inequality measures are scale-free, relative measures. Let y be income, \bar{y} is the highest observed income, $f(y)$ is the density of income, $F(y)$ is the income distribution, μ is the empirical mean income, V is the standard deviation of income, and $\phi(y) = \frac{1}{\mu} \int_0^y z f(z) dz$ is the Lorenz function. The four traditional welfare measures are the coefficient of variation (COV), V/μ ; the relative mean deviation (RMD), $\int_0^{\bar{y}} |y/\mu - 1| f(y) dy$; the Gini index, $0.5\mu \int_0^{\bar{y}} [yF(y) - \mu\phi(y)] f(y) dy$; and the standard deviation of logarithms (SDL), $\int_0^{\bar{y}} [\log(y/\mu)]^2 f(y) dy$.

The coefficient of variation attaches equal weight to transfers anywhere in the distribution. The Gini index attaches more weight to transfers at the middle of the distribution than in the tails for typical distributions (Atkinson, 1970). The standard deviation of logarithms places more weight on transfers at the lower end of the income distribution.² Atkinson notes that all these measures (and any other concave social welfare function) give the same ranking when comparing two distributions where one is a mean preserving spread of the other. However, these measures give different rankings if the mean preserving spread condition is not met.

Atkinson (1970) popularized an inequality measure that we refer to as the “Atkinson index.” This index has three strengths. First, the Atkinson index uses a single parameter to nest an entire family of social welfare functions that vary from very egalitarian to completely nonegalitarian. Second, it can be derived axiomatically given several desirable properties (Atkinson 1970; Cowell and Kuga 1981). As Dalton (1920) and Atkinson (1970) argued compellingly, any measure of inequality should be premised on a social welfare concept. They contended that a social welfare function should be additively separable and symmetric function of individual incomes.

Third, the Atkinson index has a useful monetary interpretation. Corresponding to the Atkinson index is an equally distributed equivalent level of income, y_{EDE} , which is the level of income per head that, if income were equally distributed, would give the same level of social welfare as the actual income distribution:

² One might choose between these measures based on how they treat transfers between individuals. Dalton (1920) argued that any ranking of distributions should satisfy his “principle of transfers” whereby a transfer of income from a richer person to a poorer person leads to a preferred distribution. Atkinson showed that Dalton’s concept is the same as that of a mean preserving spread. Given Dalton’s criterion, we would reject any measure that is not strictly concave such as the relative mean deviation, which is unaffected by transfers between people on the same side of the mean. Our other three traditional measures are sensitive to transfers at all income levels.

$$U(y_{EDE}) \int_0^{\bar{y}} f(y) dy = \int_0^{\bar{y}} U(y) f(y) dy,$$

where $U(y)$ is an individual's utility function. This measure is invariant to linear transformations of the utility function. Atkinson's welfare index is

$$I = 1 - \frac{y_{EDE}}{\mu}. \quad (1)$$

We can use this index to determine the percentage welfare loss from inequality. For example, if $I = 0.1$, society could achieve the same level of social welfare with only 90% of the total income if incomes were equally distributed. Our measure of welfare loss from inequality, L , the difference between the actual average income and the equally distributed equivalent level,

$$L = \mu - y_{EDE} \quad (2)$$

is a transformation of the Atkinson welfare index, Equation (1).

To impose constant relative inequality-aversion, Atkinson chose the representative utility function

$$U(y) = \begin{cases} A + B \frac{y^{1-\varepsilon}}{1-\varepsilon} & \varepsilon \neq 1 \\ \ln(y) & \varepsilon = 1 \end{cases}$$

where $\varepsilon \geq 0$ for concavity and ε represents the degree of inequality aversion. After some algebraic manipulations involving Equations (1) and (2), Atkinson obtained his welfare index for n people:

$$I_\varepsilon = \begin{cases} 1 - \left(\frac{1}{n} \sum_{i=1}^n \left(\frac{y_i}{\mu} \right)^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}} & \varepsilon \neq 1 \\ 1 - \left(\prod_{i=1}^n \frac{y_i}{\mu} \right)^{\frac{1}{n}} & \varepsilon = 1 \end{cases}. \quad (3)$$

Atkinson's index, Equation (3), equals zero when incomes are equally distributed and converges to (but never reaches) 1 as inequality increases. The index increases in ε . The larger is ε , the more weight the index attaches to transfers at the low end of the distribution and the less weight to transfers at the high end of the distribution. In the extreme case where $\varepsilon \rightarrow \infty$, the welfare measure becomes Rawlsian: Welfare depends on the income of the poorest member of society. If $\varepsilon = 0$, the utility function is linear in income and the distribution of income does not affect the welfare index: $I_\varepsilon = 0$ for any income vector. Thus, we view $\varepsilon = 0$ as a degenerate case and only look at ε that are strictly positive. Following Atkinson (1970), we assume that ε lies within the range $(0, 2.5]$.³ In our empirical work, our lowest value is $\varepsilon = 0.1$.

Data and Variable Definitions

We use a cross-section, time-series data set with 850 observations: one observation for each state in each year 1981-1997.

Income and Welfare Measures: The CPS's total income measure, “the amount of money income received in the preceding calendar year”, includes in-cash government transfers but not food stamps, other government in-kind transfers, income tax payments or tax credit received. Therefore, the CPS's definition of income does not measure a family's entire disposable income.

Fortunately, beginning at 1981, the CPS imputed the value of government transfers, tax liability and credit for each family. Data from the American Housing Survey (AHS), the Income Survey Development Program (ISDP), and the Internal Revenue Service (IRS) were combined with CPS data to create simulations of taxes paid, number of tax filing units, adjusted gross

³ In his empirical work, Atkinson only considers $\varepsilon \leq 2.5$, plots one of his diagrams between 1.0 and 2.5 and suggests that we might all agree that $1.5 \leq \varepsilon \leq 2.0$. We found that using larger ε puts so much weight on the well being of the poorest members of society that the welfare losses from any inequality are virtually equal to all of society's income.

income, and other tax characteristics for the March CPS.⁴ Based on this augmented series, we are able to construct the after-transfer, after-tax monetary income by adding the value of food stamps, tax payments, or credit of each family to the corresponding CPS income.

To adjust for family income variation due to family size, we divide the family income by the number of adults—people 18 and older—in the family (below, we examine the robustness of this assumption). Several of our inequality measures—particularly the Atkinson index where $\varepsilon > 1$ so that low incomes are weighted heavily—are very sensitive to even a single family with an income close to zero in the sense that the number of large-income observations has little effect on the index. Even though there are few such families in the sample, we deal with this sensitivity problem by using a “trimming” method based on influence function for inequality estimates (Cowell and Victoria-Feser 1996). On average, less than 0.3% of families or around 3 families in each state in a given year are dropped from the sample.⁵

For all our inequality indices, there is less after-tax income inequality than pre-tax income inequality. According to all inequality measures, both pre- and after-tax inequality increased considerably over the observation period.

Government Policies: All the government policy variables vary over time and across states except that federal income tax and disability insurance vary only over time. We use two

⁴ For details, see Measuring the Effect of Benefits and Taxes on Income and Poverty: 1979 to 1991, Current Population Reports Series P-60, No. 182. This series was not included in the official CPS March Supplement until 1992. The data for the earlier years were obtained from Unicon Research Corporation (<http://www.unicon.com>), to whom we are grateful.

⁵ See the appendix for details. To examine whether “trimming” is related to the policies of interest, we regressed the proportion of observations excluded from the sample of each state-year on the government policy variables and other control variables. None of the policy coefficients are statistically significantly different from zero.

variables, the federal marginal income tax rate for the top bracket (High Tax) and for the bottom bracket (Low Tax), to proxy the change of federal income tax over the observed period.⁶

The state-specific data on the minimum wage and maximum weekly unemployment insurance benefits were obtained from the U.S. Bureau of Labor Statistics' Monthly Labor Review, which summarizes the previous year's state labor legislation. Data on other public assistance programs are from the annual *Background Material and Data on Major Programs within the Jurisdiction of the Committee on Ways and Means* (the "Green Book").

Our minimum wage variable is the larger of the federal or the relevant state minimum wage. If the minimum wage changed during the year, we use a time-weighted average. Our Unemployment Insurance (UI) variable is the maximum weekly benefit in a state (almost all the states set the maximum coverage period at 26 weeks during the relevant period). Our disability (the inability to engage in "substantial gainful activity") insurance measure is the annual benefit.

Near the end of our observation period, the Aid to the Families with Dependent Children (AFDC) program was replaced by the Temporary Assistance to Needy Families (TANF) program, which made the eligibility standards more restrictive. TANF was enacted in August 1996 and phased in beginning in 1997. The "TANF reform" dummy variable is one for the years when each state has implemented major AFDC waivers (as a precursor to TANF) or replaced AFDC with TANF. The AFDC/TANF variable is the maximum monthly benefits for a single-parent, three-person family, while the "AFDC/TANF need standard" is the maximum income for

⁶ The tax rates were obtained from the Congressional Joint Committee on Taxation website. The number of federal income tax brackets fell from five to three in 1990 and reverted to five brackets in 1993. The thresholds for each bracket changed many times during our sample period. To be consistent across time, we use the marginal income tax for the bottom bracket and top bracket. Although the Low Tax rate and the High Tax rate are set simultaneously, their correlation is -0.52.

a single-parent, three-person family to be eligible for assistance.⁷ The AFDC/TANF eligibility standard is used for both that program and food stamps.⁸ Our food stamps measure is the maximum monthly benefit. The Supplemental Security Income (SSI) variable is the maximum monthly benefits for individuals living independently. To qualify for SSI payment, a person must meet age, blindness or other disability standard and have an income below the federal maximum monthly SSI benefit.

The Earned Income Tax Credit (EITC) is an earning subsidy for the low income working families. Beginning in middle 1980's, some states offered state EITC, usually in the form of a fixed percent of the federal EITC credit. Our EITC benefit variable is adjusted by state supplements, hence this measure also varies across both states and time. To receive the EITC, a family must report a positive earned income. The EITC maximum benefit is determined by two factors: the EITC credit rate and the minimum income requirement for maximum benefit. Our EITC Benefits variable measures the maximum benefit, which is the product of these two factors. The EITC is phased out as a family's income rises. For example, in 1997, the phaseout income range was (\$11,930, \$25,750) for a one-child family. The credit was reduced by 15.98¢ for each extra dollar earned above \$11,930 so that the benefit dropped to zero at \$25,750. Here, our EITC phaseout rate variable measures the rate, 15.98%, at which the EITC benefits is reduced over the phaseout range.

⁷ Because the AFDC benefit reduction rate for income above the need standard is 100% over the entire period, we do not include it in the model.

⁸ All AFDC/TANF families are income-eligible for food stamps. More than 90% of AFDC families usually receive food stamps (Green Book, 1996).

Macroeconomic and Demographic Variables: We include two macroeconomic variables to control for economic conditions. The gross domestic product (GDP)⁹ and state unemployment rates are from the Bureau of Labor Statistics' website. In addition to state dummy variables, we include annual state-level demographic characteristics obtained from the CPS: the percentage of families where at least one adult member has a high school degree or more education, the percentage of female-headed families, the percentage of the state's population in various age groups (<18, 18-29, the residual group, and ≥ 60), the percentage of families with at least one child younger than 6, and the average family size.

Table 1 shows the unit of measure, mean, standard deviation, minimum, and maximum for all our explanatory variables other than the state dummies. All monetary variables are expressed in real 1981 dollars using the Consumer Price Index. We measure the minimum wage in dollars and all other monetary policy variables in thousands of dollars.

Regression Model

Following the usual practice of the policy evaluation literature, we treat inter-temporal and cross-state variation in state tax and welfare policies as the sources of identification of the policy effects. We include in our model all the major government programs that directly or indirectly transfer income to the poorest members of society and that vary in real terms over time or across states during our sample period. The government tax and transfer programs directly affect family income. The minimum wage, disability insurance, and unemployment insurance have direct effects on people's received income and indirect effects on their transferred income because other government transfer programs are contingent on income. Moreover, all the policies

⁹ We use national rather than state-level GDP to avoid circularity. As we report in the robustness section, we experimented by replacing the GDP with the gross state products and obtained very similar results. We also included state and (random) year effects to capture cyclical conditions and found similar results.

affect people's labor market behaviors and therefore their income (see Wu 2003 and references therein).¹⁰

We examine the correlation of the traditional inequality measures and the various Atkinson indexes ranking over our 850 state-year observations. The correlations between the inequality rankings from Atkinson indexes with ε in the range $(0, 1]$ and the relative mean deviation, the coefficient of variance, and the Gini index are virtually one. The standard deviation of logarithms is almost perfectly correlated with the Atkinson index where $\varepsilon = 1.5$. Therefore, by choosing an appropriate value of ε , we could use I_ε to proxy the inequality ranking from the traditional inequality indexes. Nonetheless, we use all the welfare measures in our analyses.

Using observations for state i in year t , we regress our various inequality indices, W_{it} , on state dummy variables, D_i (49 out of 50 states), government policy variables, macroeconomic variables, and our seven state-level demographic variables, Z_{itn} :

$$\begin{aligned} W_{it} = & \alpha_0 + \sum_{s=1}^{49} \lambda_s D_s + \alpha_1 \text{Low Tax}_t + \alpha_2 \text{High Tax}_t + \alpha_3 \text{Min. Wage}_{it} \\ & + \alpha_4 \text{UI}_{it} + \alpha_5 \text{SSI}_{it} + \alpha_6 \text{AFDC/TANF}_{it} + \alpha_7 \text{AFDC/TANF Need}_{it} \\ & + \alpha_8 \text{TANF Reform}_{it} + \alpha_9 \text{Disability Insurance}_t + \alpha_{10} \text{Food Stamps}_{it} \\ & + \alpha_{11} \text{EITC Benefit}_{it} + \alpha_{12} \text{EITC Phaseout Rate}_t + \alpha_{13} \text{GDP}_t \\ & + \alpha_{14} \text{Unemployment Rate}_{it} + \sum_{n=1}^7 \beta_n Z_{itn} + \zeta_{it}, \end{aligned} \quad (4)$$

where ζ_{it} is the error term.

We estimate this fixed-effect model using generalized least squares allowing for panel specific first-order autoregressive errors. We report White's heteroskedasticity-consistent

¹⁰ Many of the policies rarely changed during our sample period and hence it is reasonable to view them as predetermined. It is difficult to imagine that variations in income distributions within states affect federal policies; however, state policies could be endogenous if state governments respond to changes in state income inequality. We conduct a Hausman test for the exogeneity of the current policy variables using the previous year's state (predetermined) policy variables as instruments for the test. The Hausman test fails to reject the null hypothesis that the current policy variables are exogenous to the dependent variable for each of the reported models.

standard errors corrected for the panel structure, where the disturbances are assumed to be heteroskedastic and contemporaneously correlated across panels (Beck and Katz 1995).

We regress each of the pre- and post-tax inequality measures (the four conventional indexes and various Atkinson indexes) on the major government policies, macroeconomic conditions, and demographic characteristics for each state-year for both pre-tax and after-tax income. Because our after-tax income includes the value of food stamps, tax payments and credits to the CPS pre-tax, after-transfers income, these programs presumably should have more profound effects on after-tax income inequality than on pre-tax income inequality. However, the pre-tax and post-tax regressions differ relatively little qualitatively. Consequently, we report the post-tax regressions in detail and note the difference with the pre-tax regressions.

Policy Effects: For all regressions on inequality measures, a positive coefficient indicates that an increase in the corresponding variable reduces equality, while a negative coefficient indicates that the variable has an equalizing effect.¹¹ We report the regression results for the traditional inequality measures and several Atkinson measures in Table 2. The results for the coefficient of variation and relative mean deviation measures are close to those for the Atkinson index with ε in $(0,1]$, while the results for standard deviation of logarithms resembles those for $I_{1.5}$. All the equations fit extremely well as indicated by the reported R^2 .

Similarly in Figure 1, we show how changes in policy variables affect after-tax Atkinson indexes (I_ε) by plotting elasticities with respect to each policy variable for ε between 0.1, a value

¹¹ The Atkinson and Gini indices are constrained to lie between 0 and 1, where 1 reflects complete inequality. In all our Gini and Atkinson regressions of Equation (4), the predicted values lie between zero and one, so we do not need to use a tobit-like method.

near 0, and 2.5 at 0.25 increments.¹² In the figures, a circle indicates that the coefficient is not statistically significantly different from zero, an asterisk shows that the coefficient is statistically significantly differ from zero at the 10% level, and a square reflects that it is statistically significantly differ from zero at the 5% level. A remarkable feature of the plots is that all those coefficients that are statistically significant (and even most of the others) have the same sign across various values of ε . [To save space, we do not show the statistically insignificant elasticities for the three AFDC/TANF variables.]

Taxes and EITC: Raising the marginal tax rates increases after-tax equity. As Table 1 shows, an increase in either the low or high marginal tax rate statistically significantly reduces inequality at the 5% level for all the welfare measures (except the COV measure for the Low Tax). Using the pre-tax measures, both the tax rate variables have quantitatively smaller but still statistically significant equalizing effects.

Figure 1 illustrates that an increase in the marginal tax rate of the bottom tax bracket (“low tax”) has a greater equalizing effect the larger is ε (the more weight the Atkinson measure places on the least well-off member of society). For the marginal tax rate of the top income bracket (“high tax”), the equalizing effect is greatest for low values of ε (and virtually the same for all ε greater than 1). The income tax for the bottom tax bracket has a relatively large equalizing effect, in part because the majority of the population is affected by the change in the tax rate of the bottom bracket while only a small portion of the population is affected by the tax rate of the top bracket.

Increasing the Earned Income Tax Credit benefit reduces after-tax income inequality. The coefficient for our EITC maximum benefit variable (the product of the credit rate and the income

¹² Let p_i be the i^{th} policy variable, the elasticity of I_ε with respect to change of p_i is calculated as $\hat{\beta}_i \bar{p}_i / \bar{I}_\varepsilon$, where $\hat{\beta}_i$, the estimated coefficient for p_i , is an estimate of $\partial I_\varepsilon / \partial p_i$.

threshold for the maximum benefit) is statistically significantly negative for the four traditional measures and the Atkinson measures for $\varepsilon \leq 1.75$. This result is consistent with the literature, which observes that, unlike the AFDC/TANF and Food Stamps programs, the EITC may have desirable incentive effects. Eissa and Liebman (1996), Meyer and Rosenbaum (2001), and Wu (2003) show that the EITC increased the labor supply of single mothers. Moreover, studying the EITC's effect on individual income, Neumark and Wascher (2001) and Wu (2003) find that the EITC played an important role in fighting poverty.

The coefficients for the phaseout rate of the EITC, the implicit tax rate for income within the phaseout range, are statistically significantly positive for all measures except $I_{2.5}$, which suggests that an increase in the phaseout rate statistically significantly reduces equality. Theory predicts that the phaseout rate may have disincentive effects on the labor supply and therefore negative impacts on the income of the working poor. This observation is confirmed by some previous studies. For example, Eissa and Hoynes (1998), who model the labor supply of couples jointly, find that the EITC reduced the amount of labor that wives supply. Wu (2003) examines the credit/phasein rate and phaseout rate of the EITC separately and reports that increasing phaseout rate reduced the labor supply of single mothers.

The elasticity of the inequality to the EITC variables appears to decrease with ε of the Atkinson index in Figure 1, so that the EITC effect diminishes as more weight is placed on the lower end of the income distribution. A possible explanation for this result is that the EITC, which is an earnings subsidy, benefits those already working, most of who are not at the bottom of the income distribution. For example, in 1997, the phasein range of the EITC covers the first decile of the U.S. household income distribution (including single-mother families and the all

other family category) and the next two deciles largely coincide with the constant and phaseout range of the EITC combined, the income range where most of the EITC benefits accrue.

A second explanation, which only applies to the phaseout rate, is that the change in the phaseout rate will only affect those in the phaseout range, whose income are generally above the 15th percentile of the income distribution. Therefore, the magnitude of the EITC effects due to the phaseout rate does not necessarily increase as we place more weight on the lower end of the income distribution.

Minimum Wage: For pre-tax income inequality, the minimum wage coefficient is statistically significantly positive for all inequality measures (not shown in Table 2). For the after-tax inequality measures, the minimum wage coefficient is statistically significant at the 5% level for SDL (Table 2) and Atkinson indexes for $\varepsilon \geq 1.25$ (Table 2 and Figure 1). Thus, an increase in the minimum wage reduces after-tax equality if we weight the lower income portion of the post-tax income distribution relatively heavily.

The minimum wage, unlike transfer programs, is not a means-test program. Any working person may benefit from an increase of minimum wage regardless of their family income. As Burkhauser, et al. (1996) observed, minimum-wage workers are evenly distributed across all family income groups, in large part because teenage workers belong to families in all income strata. Neumark, et al. (2000) suggested that the net effect of a minimum wage increase resembles “income redistribution among low-income families than income redistribution from high to low-income families.” Moreover, a minimum wage hike may reduce income of poor

families relative to wealthier families since the disemployment effect is disproportionately concentrated among low-income families.¹³

Social Insurance Programs: The social insurance programs have differing effects. Unemployment insurance does not have a statistically significant effects except for the Atkinson index with $\varepsilon \geq 2$ (where we heavily weight the low end of the income distribution), where UI has a disequalizing effect that is statistically significant at only the 10% level. As with the minimum wage, unemployment insurance does not target low-income families and many of its beneficiaries are from relatively affluent families.

Disability Insurance statistically significantly reduces inequality for Atkinson measures where $0.25 \leq \varepsilon \leq 1.5$ (relatively low weight on the poor). Supplemental Security Income statistically significantly (at the 10% or 5% levels) reduces inequality for Atkinson measures where $\varepsilon \geq 1.75$. The SSI beneficiaries are the aged, blind, and disabled and the beneficiaries of the disability insurance are those disabled people who are unable to engage in “substantial gainful activity” (Green Book, 1996). SSI covers more than 90% of civilian workers, unlike traditional welfare programs (AFDC/TANF), which primarily benefit female-headed families.

Transfer Programs: The AFDC/TANF transfer programs do not have a statistically significant effect, whereas food stamps tend to reduce equality for some measures. None of the three AFDC/TANF income transfer program variables have a statistically significant effect for any after-tax inequality measure (except the TANF reform variable for COV and the AFDC/Need for Atkinson indexes with $1.5 \leq \varepsilon \leq 2$). This lack of a result presumably is the result of disincentive effects offsetting the direct transfers. The studies Moffitt (1992) reviewed

¹³ On the other hand, the reduction in real minimum wage may contribute to the rise of wage dispersion in the lower portion of wage distribution (see DiNardo, et al. 1996, Lee 1999 and Teulings 2001).

unequivocally show that the AFDC program generates a nontrivial work disincentive. The AFDC benefit levels are about the same as a woman would receive if she works a full-time in a minimum-wage job for a full year. In addition, the AFDC program benefit reduction rate is 100% for income over the threshold for maximum benefit. Thus, beneficiaries have no incentive to work additional hours once their incomes reach the threshold for maximum AFDC benefit, and some people may reduce the number of hours they work to become eligible for the program.

The food stamps program statistically significantly reduces equity according to the SDL and the Atkinson measures for $\varepsilon \geq 1.25$. As Leonesio (1988) notes, in-kind transfer programs have the same disincentive effects as cash transfer programs. Fraker and Moffitt (1988) found that the food stamps program has a modest disincentive effect on labor supply. The food stamps program is one of the top three most expensive welfare programs, along with AFDC/TANF and EITC. Unlike the other two programs, which mostly benefit the female-headed families, all families are eligible for food stamps if their family income is less than a threshold amount. Hence, when we examine the policy effects on the income distribution of the entire population, the difference in coverage may partially explain why the food stamps program has more substantially redistributes income than does the AFDC/TANF program.

Demographic and Macro Effects: As with the policy variables, the qualitative effects of the demographic and macroeconomic control variables vary little across the inequality measures. Increases in the GDP and the unemployment rate tend to increase income inequality. An increase in the average education level in a state has a statistically significant equalizing effect for all measures except $I_{2.5}$.¹⁴ The higher the share of female-headed families, the less equal is income. This result is consistent with the literature (e.g., Gottschalk and Danziger 1993) that the

¹⁴ Moretti (2000) shows that an increase in average education has a positive spillover effect on the earnings of all groups.

change of family structure, especially the dramatic increase of female-headed family, substantially contributed to the rise in income inequality over the last two decades.

We find a systematic pattern in the state dummy coefficients. We regressed the coefficients for state dummies from each inequality equation on six regional dummies. For the traditional measures and the Atkinson indexes for $\epsilon < 2$, two regions had statistically significantly higher coefficients (less equality) than the other four regions. The largest regional effect is for the South Central region followed by the South Eastern region. This pattern is consistent with Madden's (2000) study of variations in inequality across U.S. metropolitan statistical areas, which finds the greatest inequality in the South Central region.

Robustness of Results

To check the robustness of our reported results, we conducted a series of experiments with alternative estimation methods and another series with different model specifications (available from the authors). To check for a potential multicollinearity problem, we calculated the condition number, which is 174 for all the right-hand-side variables excluding the state dummies and 592 with the state dummies.¹⁵ Given the possibility of collinearity, we re-estimated our model using the generalized maximum entropy (GME) method of Golan, Judge and Miller (1996). GME is a robust technique that works well with ill-conditioned problems. The GME estimated coefficients were very close to the OLS estimates but tended to be slightly smaller in absolute value (which should be expected because GME is a shrinkage estimator).

Because some key policies vary over time but not across states, we cannot estimate fixed-year effects. Instead, we estimated a mixed-effects model, treating the state effects as fixed effects and year effects as random effects. The estimates with random year effects and those

¹⁵ Green (1997) suggests that there may be a collinearity problem if the condition number exceeds 20.

without random year effects are close. The estimates of the policy variables, including those policies varying only over time, are not sensitive to the inclusion of random year effects. Moreover, we rejected the hypotheses of random year effects at the 95% level for Atkinson index with $\varepsilon > 1$.

To see how sensitive our results are to our specification assumptions, we conducted robustness experiments corresponding to each of our main assumptions. First, we normalize the inequality measures by dividing each family's income by the number of adults in the family. Two possible alternative normalizations are to divide family income by all the family members (including children) or to make no adjustment and use family income. Our qualitative results are not sensitive to these normalizations. The average correlation coefficient between our original Atkinson indexes and the two alternatives are 0.81 and 0.85 respectively and the estimated coefficients are virtually the same.

Second, we examined how controlling for macroeconomic variables, aggregate demographic variables and state dummies affects our results by conducting three experiments. In the first experiment, we estimated the regression without the state dummies. All the coefficients that were significantly different from zero in our original setup remain so. The major changes were that AFDC/TANF coefficients became significantly negative for some range of Atkinson index and the disequalizing effects of minimum wage became more statistically significant.

Next, we estimated the regression omitting the state macroeconomic and demographics variables. Our results are virtually the same as in our full regression.

Further, we estimated the regression using only the policy variables. The High Tax, EITC Benefits, and EITC Phaseout Rate coefficients were close to those of the full regression, while

the coefficients of the Low Tax became statistically insignificant over the entire range of the Atkinson index.

Finally to examine how sensitive our results are to changes in estimation method and the specification (including the choice of inequality measure), we use a semi-parametric approach to estimate the policy impact on the entire income distribution. Our semi-parametric estimates are qualitatively and quantitatively close to those parametric results reported above. The results are available from the authors upon request.

Welfare Assessment of Policy Effects

So far, we have shown that the directions of policies' effects on income inequality are generally consistent across inequality measures. How do the magnitudes of these vary? There is no simple way to compare the magnitude of the effects using traditional measures. However, comparisons across the Atkinson measures are straight forward because they have a dollar value interpretation. More importantly, by varying the implicit inequality aversion index of the Atkinson index, one can assess the welfare effects of policy changes for a wide range of social welfare functions under Atkinson's unified framework.

We illustrate the magnitude of the welfare effects of some key government policy variables in our analysis using the change in the welfare loss, $L = \mu - y_{EDE}$, Equation (2), which is the actual average income, μ , less the equally distributed equivalent level of income, y_{EDE} . According to our estimates, the equally distributed equivalent level of income, $y_{EDE} [= \mu(1 - I_\varepsilon)]$ is 99, 90, 81, 58, or 44% of the average actual income when the Atkinson index parameter $\varepsilon = 0.1, 0.5, 1, 2$, or 2.5 . For example if $\varepsilon = 1$, society could achieve the welfare associated with the actual income distribution if every adult's income equaled 81% of the actual average income.

For example, if we raise the 1997 level of the Low Tax rate by 10%, from 15% to 16.5%, the Atkinson index changes to $\hat{I}'_\varepsilon = \hat{I}_\varepsilon + 0.165 \times \hat{\beta}_{\text{Low Tax}}$, where \hat{I}_ε is the estimated actual Atkinson index for 1997 family income and $\hat{\beta}_{\text{Low Tax}}$ is the estimated coefficient for the Low Tax. Assuming that the change in taxes does not have any other general equilibrium effects, the change in welfare loss from lack of equality is [using Equation (1)]

$$\Delta L = (\mu_{97} - \hat{y}_{EDE}) - (\mu_{97} - \hat{y}'_{EDE}) = \mu_{97} [(1 - \hat{I}'_\varepsilon) - (1 - \hat{I}_\varepsilon)] = \mu_{97} (\hat{I}_\varepsilon - \hat{I}'_\varepsilon)$$

where $\mu_{97} = \$21,068$ (in 1997 dollars) is the arithmetic mean of 1997 family incomes.

For $\varepsilon = 1$, a 10% increase in the Low Tax rate, High Tax rate, or EITC benefits increases the average welfare by \$100, \$46, or \$59.¹⁶ If we multiply these average income effects by the U.S. adult population in 1997 (198.2 million), we find that the welfare improvement from each of these experiments is respectively \$20 billion, \$9 billion, and \$12 billion. Similarly, a 10% increase in the minimum wage and the EITC phaseout rate increases the overall welfare loss by \$9 billion and \$30 billion respectively. That is, if we reduce the minimum wage by 10%, we could achieve the current welfare level with \$9 billion less national income.

We calculated the welfare effects of policy changes for $\varepsilon \neq 1$ similarly, which we report in Table 3. Among the welfare improvement that are statistically significantly different from zero when $\varepsilon = 2.5$, Low Tax has the largest equalizing effect and minimum wage has the greatest disequalizing effect. Table 3 shows that when $\varepsilon = 2.5$, Low Tax, the minimum wage, and SSI have very large effects—up to an order of magnitude larger than when $\varepsilon = 1$.

¹⁶ The High Tax effects are smaller than those for the Low Tax because the Atkinson index (at least for $\varepsilon \geq 1$) places more weight on the low end of the income distribution than on the high end. Further, 57% of 1997 tax filers are in the lowest tax bracket.

Our measure of a policy's welfare effect is a dollar value interpretation of change in the aggregate social welfare and depends on the choice of ϵ in the Atkinson index, which captures the degree of inequality aversion. This estimate is based on the distributions of individual realized income, which reflects the impact of policy changes on both the benefit calculation (the direct/mechanical effect) and the induced responses in labor market behavior (the indirect/behavioral effect). Therefore, the reported welfare benefit/cost should not be confused with the traditional benefit/cost analysis, which does not take into account either the social welfare function or the potential behavior effects of changes in policies.

Conclusion

What can the government do to reduce income inequality? To answer this question, we examine the effects of the major government tax, social insurance, and redistribution policies on all the commonly used inequality measures: the coefficient of variation of the income distribution, the relative mean deviation of income, the standard deviation of logarithms of income, the Gini index, and the Atkinson index for various values of its key parameter. We use the variation of various government programs across states and over time (1981-1997) to estimate the policies' effects on the income distribution controlling for macroeconomic and aggregate demographic variables. Our study is the first to examine the distribution interaction effects of all the major government anti-poverty policies on the entire income distribution.

We draw four main conclusions. First, it is practical to study the distributional effects of government programs because almost all the estimated results are qualitatively identical across common inequality measures. Moreover, we find that the results are nearly identical for a variety of model specifications and estimation techniques.

Second, an effective way to make the income distribution more equitable is to use taxes. The marginal tax rates have larger equilibrating welfare effects than do social insurance or direct transfer programs. The Earned Income Tax Credit has smaller but still statistically significant desirable effects.

Third, the minimum wage laws and direct transfer programs have no statistically significant effects or reduce equality. For Atkinson inequality measures that place substantial weight on the well being of the poor ($\varepsilon \geq 1.5$), a 10% increase in the minimum wage statistically significantly lowers welfare (as measured by Atkinson's equally distributed equivalent level of income measure) by \$22 to \$97 billion. The AFDC/TANF program has no net effect, while the food stamp program either has no effect or reduces equality. Presumably these redistribution programs are ineffective because their disincentive effects offset the direct transfers.

Fourth, the social insurance programs tend to have relatively small effects except for SSI. Unemployment has a small negative distributional effect, which is statistically significant for measures that weight the poor's income heavily. Disability Insurance tends to have small positive effect. Supplemental Security Income has a sizeable, statistically significant positive effect for measures that weight the poor's income heavily.

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Appendix: Trimming

All the income inequality indexes, including the Gini index reported by Census Bureau based on March CPS, are calculated using strictly positive incomes. We find that including a few near zero, positive income observations has little effect on the Atkinson index if $\varepsilon < 1$; but has a substantial effect if $\varepsilon > 1$ that does not vanish as the sample grows extremely large. Further, our regression analyses are sensitive to whether we include a few near zero observations.

Therefore, we want to remove these few low-income observations because they disproportionately dominate the indexes. Rather than arbitrarily removing obvious outliers, we use a sensitivity analysis of our inequality estimates to “trim” the data systematically for each state subsample in each year. We employ an influence function for inequality estimates (Cowell and Victoria-Feser 1996) to quantify the importance of an infinitesimal amount of contamination upon the value of statistic,

$$\text{IF}(x, \mathbf{y}, \mathbf{w}) = \frac{x^\alpha + \sum_{i=1}^n w_i \frac{y_i^\alpha}{n} \left(\alpha - 1 - \frac{\alpha x}{\mu(y)} \right)}{(\alpha^2 - \alpha) \mu(y)^\alpha}$$

where \mathbf{y} is the income vector with \mathbf{w} being the weights, x is the data point of interest at the lower end of the income distribution, and $\alpha = 1 - \varepsilon$ for an Atkinson index I_ε . When $\alpha < 0$ or $\varepsilon > 1$ for I_ε , if x is close to zero, the first term in the numerator becomes extremely large and this single observation may have overwhelming impact upon the estimation of inequality index.

For each state subsample in a year, we start with an x that is the minimum positive family income and then incremented by 10 until the change of influence function is less than 10%. This technique is not very sensitive to the variation in income distribution across states or years, in the sense that the number of observations dropped does not vary much across states and years. We

also experimented with value 5% and 15%. The results are very close to those reported here. Therefore, we conclude that our inequality estimates and regression analysis are not sensitive to the stopping rule.

Table A.1 summarizes the properties of the truncation points, number of families dropped, and the share of total number of observations dropped for an individual state subsample in a given year. On average, we exclude about three families (the average is 3.08 in “Mean” column), or less than 0.3% of observations from each state-year subsample. The “Minimum” column shows that the smallest number of families we dropped was one, which we did for 346 individual state-year subsamples. The most we dropped (“Maximum” column) was 43 in California in 1992 (out of 6,164 families). Compared to some common practice employed in traditional studies, such as removing the families with income below the first percentile or some arbitrarily chosen number, the influence function approach removes a smaller number of observations from the sample. This data-based approach is both consistent and flexible in the sense that a universal standard is used to determine what constitutes the outliers while the threshold for outliers is different in each state-year, depending on the distribution of the data in each subsample.

Table A.1: Summary Statistics of Sensitivity Analysis

	<i>1st</i> <i>Quarter</i>	<i>Median</i>	<i>Mean</i>	<i>3rd</i> <i>Quarter</i>	<i>Maximum</i>
	<i>Minimum</i>				
Value of truncating point	50	50	185	211	300
Number of families dropped	1	1	2	3	43
Percent of families dropped	0.04	0.14	0.21	0.29	1.41

To examine whether there is a systematic policy or state fixed effects on this trimming procedure, we regress the proportion of families dropped in each state-year subsample on the set

of regressors as in Equation (4). None of the coefficient, including those for the state dummies, is statistically significantly different from zero at 5% level. The R^2 is 0.052.

Table 1: Summary Statistics, 1981-1997

<i>Variables</i>	<i>Unit</i>	<i>Mean</i>	<i>Std. Var</i>	<i>Minimum</i>	<i>Maximum</i>
Low Tax	Percent	0.14	0.02	0.11	0.15
High Tax	Percent	0.41	0.11	0.28	0.69
EITC Benefits	\$1,000/year	0.86	0.36	0.48	2.07
EITC Phaseout Rate	Percent	0.14	0.04	0.10	0.21
Minimum Wage	Dollar/year	3.09	0.27	2.70	4.24
Unemployment Insurance	\$1,000/week	0.19	0.08	0.06	0.72
SSI	\$1,000/month	0.32	0.05	0.26	0.63
Disability Insurance	\$1,000/year	0.31	0.04	0.24	0.38
AFDC/TANF	\$1,000/month	0.29	0.12	0.08	0.68
AFDC/TANF Need	\$1,000	0.43	0.15	0.17	1.30
Food Stamps	\$1,000/month	0.18	0.03	0.09	0.30
GDP	Trillion dollars	4.28	0.52	3.38	5.17
State Unemployment Rate	Percent	0.07	4e-4	0.02	0.18
Education	Percent	0.87	0.05	0.70	0.97
Female-Headed Family	Percent	0.24	0.07	0.09	0.45
Age < 18	Percent	0.28	0.03	0.21	0.39
Age 18-29	Percent	0.18	0.02	0.11	0.28
Age ≥ 60	Percent	0.16	0.03	0.05	0.23
Families with Children < 6	Percent	0.16	0.03	0.11	0.29
Ave. Family Size	Number of persons	2.48	0.15	2.17	3.05

Table 2: Regression Results For Conventional Measures and Atkinson Measures
 (The top number is the coefficient and the bottom number is the t -statistic)

	<i>GINI</i>	<i>COV</i>	<i>RMD</i>	<i>SDL</i>	<i>I</i> _{0.1}	<i>I</i> _{0.5}	<i>I</i> ₁	<i>I</i> _{1.5}	<i>I</i> ₂	<i>I</i> _{2.5}
Low Tax	-0.25	-0.25	-0.41	-1.34	-0.02	-0.14	-0.32	-0.57	-0.98	-1.47
	-3.95	-0.66	-4.75	-7.81	-2.25	-3.38	-5.19	-7.84	-8.00	-6.60
High Tax	-0.05	-0.18	-0.07	-0.18	-0.01	-0.03	-0.06	-0.08	-0.12	-0.16
	-4.00	-2.10	-4.02	-4.91	-3.06	-3.61	-4.39	-5.19	-4.35	-3.52
Min. Wage	3e-3	-0.02	0.01	0.04	1e-3	5e-3	0.01	0.02	0.04	0.08
	0.52	-0.98	0.76	2.05	0.04	0.56	1.35	2.08	2.74	3.32
UI	0.01	0.03	0.01	0.03	1e-3	0.01	0.01	0.02	0.05	0.08
	0.98	1.05	0.43	0.88	1.03	1.16	1.12	1.25	1.86	1.93
SSI	-0.01	-0.18	-4e-3	-0.08	-4e-3	-0.01	-0.02	-0.06	-0.27	-0.56
	-0.27	-1.32	-0.08	-0.60	-0.95	-0.66	-0.41	-1.04	-2.73	-3.23
AFDC/TANF	-0.02	0.02	-0.04	0.04	0.00	-0.01	-0.01	0.01	0.09	0.13
	-0.92	0.18	-1.14	0.43	-0.57	-0.62	-0.36	0.30	1.26	1.14
AFDC/TANF Need	0.01	-0.01	0.01	0.04	1e-3	2e-3	0.01	0.02	0.03	0.02
	0.91	-0.55	1.22	1.88	0.46	0.74	0.85	1.84	1.69	0.76
TANF Reform	-2e-3	0.03	-0.01	-0.02	1e-3	-1e-3	-4e-3	-0.01	-0.01	-0.01
	-0.94	2.74	-1.44	-1.72	0.33	-0.57	-1.31	-1.47	-1.27	-0.77
Disability Insurance	-0.04	-0.15	-0.05	-0.11	-0.01	-0.02	-0.04	-0.05	-0.01	0.02
	-1.78	-1.20	-1.60	-1.81	-1.60	-1.80	-2.03	-1.81	-0.26	0.22
Food Stamp	0.03	-0.26	0.06	0.43	-2e-3	0.01	0.07	0.16	0.27	0.16
	0.78	-1.27	0.99	2.14	-0.25	0.43	1.33	1.96	1.85	0.66
EITC Benefit	-0.02	-0.08	-0.03	-0.04	-3e-3	-0.01	-0.02	-0.02	-0.01	0.01
	-3.34	-2.20	-3.24	-2.20	-2.82	-3.07	-3.10	-2.49	-0.87	0.27
EITC Phaseout Rate	0.36	2.00	0.43	0.71	0.06	0.23	0.34	0.36	0.33	0.20
	6.50	6.24	5.68	4.43	6.67	6.60	6.25	5.31	2.83	1.01
GDP	0.02	0.06	0.02	0.05	2e-3	0.01	0.01	0.02	0.04	0.06
	2.68	2.02	2.77	2.34	2.42	2.52	2.53	2.64	2.95	2.75
Unemployment Rate	1e-3	3e-3	1e-3	2e-3	1e-3	1e-3	1e-3	1e-3	2e-3	4e-3
	1.42	2.72	1.34	1.73	2.14	1.87	1.88	2.18	2.33	2.69
Education	-0.18	-0.49	-0.28	-0.59	-0.02	-0.09	-0.17	-0.24	-0.22	-0.03
	-6.24	-3.94	-6.14	-4.59	-5.50	-5.54	-5.24	-4.81	-2.68	-0.26
Female-headed Family	0.10	0.23	0.16	0.37	0.01	0.06	0.11	0.15	0.17	0.18
	5.00	2.86	4.92	3.92	4.66	4.84	4.60	3.77	2.37	1.59
Age < 18	-0.10	-0.13	-0.18	-0.34	-0.01	-0.04	-0.08	-0.16	-0.17	-0.20
	-1.38	-0.43	-1.67	-0.97	-0.69	-0.87	-0.94	-1.08	-0.66	-0.49
Age 18-29	-0.08	0.07	-0.15	-0.36	-4e-3	-0.03	-0.08	-0.15	-0.17	-0.22
	-1.55	0.28	-2.11	-1.52	-0.59	-1.02	-1.45	-1.52	-0.90	-0.74
Age \geq 60	0.06	0.33	0.08	-0.21	0.01	0.03	0.01	-0.08	-0.14	-0.03
	1.21	1.32	1.00	-0.84	1.34	0.89	0.15	-0.80	-0.73	-0.10
Children < 6	0.08	0.11	0.14	0.21	0.01	0.03	0.06	0.12	0.24	0.42
	1.54	0.57	1.89	0.94	0.71	0.91	1.03	1.28	1.57	1.97
Ave. Family Size	0.03	0.13	0.05	0.06	0.01	0.02	0.02	0.02	0.01	0.02
	3.48	3.22	3.42	1.41	3.87	3.29	2.24	1.11	0.28	0.36
\bar{R}^2	0.99	0.94	0.98	0.95	0.96	0.97	0.97	0.97	0.91	0.88
ρ	0.20	0.08	0.21	0.14	0.17	0.19	0.19	0.13	-0.01	-0.09
D.W.	1.83	1.89	1.82	1.85	1.85	1.84	1.84	1.85	1.85	1.86

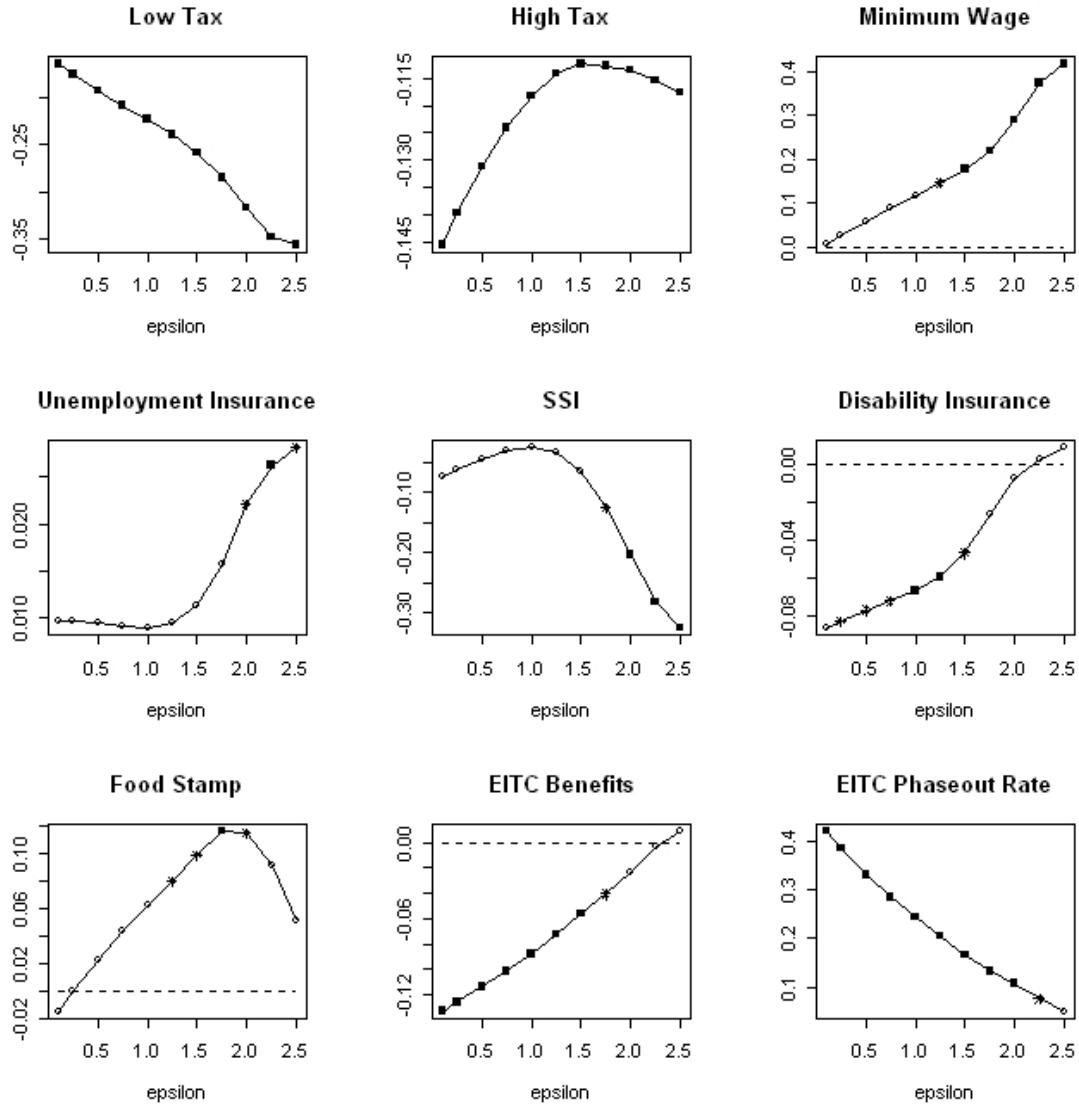
Table 3: Welfare Improvement (in \$billions) for a 10% Increase in a Given Policy Level

	$I_{0.1}$	$I_{0.5}$	I_1	$I_{1.5}$	I_2	$I_{2.5}$
Low Tax	1.47**	8.53**	19.90**	35.63**	61.42**	92.08**
High Tax	1.13**	5.07**	9.20	13.49	19.16	26.45
Min. Wage	-0.04	-2.33	-9.45	-21.89**	-50.48**	-97.45**
Unemployment Insur.	-0.01	-0.49	-0.92	-1.79	-4.83*	-8.17*
SSI	0.59	1.79	2.06	8.03	35.18**	74.75**
AFDC/TANF	0.16	0.80	0.91	-1.22	-9.02	-13.89
AFDC/TANF Need	-0.06	-0.42	-0.85	-2.88*	-5.49*	-4.13
Disability Insurance	0.70	3.09*	5.41**	5.87*	1.37	-2.02
Food Stamp	0.13	-0.95	-5.31	-12.95*	-21.53*	-12.94
EITC Benefit	1.78**	7.54**	11.70**	11.59**	6.89	-3.58
EITC Phaseout Rate	-5.23**	-20.34**	-30.10**	-31.66**	-28.79**	-17.88

** Statistically significantly different from zero at 5%.

* Statistically significantly different from zero at 10%.

Figure 1: Estimated Elasticities of Atkinson Index with respect to ϵ in $(0, 2.5]$



Note: Squares (asterisks) indicate coefficients that are statistically significantly different from zero at the 5% (10%); circles indicate coefficients not significantly different from zero. Policies where no coefficient was significantly different from zero are not shown in this figure.