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Effects of Government Policies on Income Distribution and Welfare

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Abstract

A variety of parametric and semiparametric models produce qualitatively similar estimates of government policies' effects on income distribution and welfare (as measured by the Gini, standard deviation of logarithms, relative mean deviation, coefficient of variation, and various Atkinson indexes). Taxes and the Earned Income Tax Credit are an effective way to redistribute income to the poor and raise welfare. The minimum wage lowers welfare. Social insurance programs have little effect except for Supplemental Security Income, which raises welfare. Transfer programs (AFDC/TANF and food stamps) either have no statistically significant effect or lower welfare.

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Do federal and state taxes, minimum wage laws, social insurance policies, and transfer programs raise welfare by redistributing income? Asking this question may seem pointless because the answer may vary with the measure of equity used. However, we show that all the well-known equity or welfare measures give the same qualitative answer.[1] Using both parametric and semi-parametric techniques and data from the fifty states from 1981 to 1997, we show that marginal 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 some of these other programs— particularly the minimum wage—have undesirable welfare effects.

We examine the effects of eleven major government policies on welfare using all the common, traditional welfare 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 eleven government policy variables, we examine how changes in macro conditions and demographic variables over time and across the fifty states affect welfare. Strangely, most earlier 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 and the operation of the social welfare system, the same assessment calculus can yield different

[1] Dalton (1920) suggested that all common welfare measures would give the same rankings (level) across countries "in most practical cases." However, Ranadive (1965) and 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.

results in different settings." Moreover, most previous studies of government programs do not take the next step of using a welfare measure to ascertain whether the program makes the income distribution more or less equal. Rather than focus on only the income 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 welfare measures. Then we use standard parametric models to examine how policies, macro conditions, and demographics affect each of the welfare measures. We examine the robustness of our results to various estimation technique and alternative specifications. Next, we determine the dollar-denominate welfare magnitude of the various policies. Finally, we use semi-parametric techniques to examine how policies, macro conditions, and demographics affect the income distribution directly.

Literature

The evolution of U.S. redistribution and anti-poverty policies during our sample period, 1981 to 1997, is described by Mitrusi and Poterba (2000) for tax policies and by Meyer and Rosenbaum (2000) for major government anti-poverty policies. Typically tax studies (such as Bradford 1995, 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., Schultz 1969 and Thurow 1970) emphasized the impacts of macroeconomic conditions. More recent studies (see Bishop, Formby and Sakano 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 focus on the behavior effects of these polices, such as on labor supply, participation, turn over, and family structure (see, for example, the extensive survey in Moffitt 1992). Unfortunately, few of these studies of anti-poverty policies explicitly considered their welfare effects. Card and Kruger (1995) and Neumark, Schweitzer and Wascher (1998) studied the distributional effects of minimum wage on family income distribution. Liebman (2000) examined the welfare impact of the Earned Income Credit. Moreover, virtually all the existing 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 welfare measures as well as the Atkinson index. All of our welfare measures are "relative" measures that are scale free — they have been normalized by the mean. In defining our welfare measures, we let y reflect income, y is the highest observed income, $f(y)$ is the density of income, $F(y)$ is the distribution, μ is the empirical mean income, V is the standard deviation of income, and $\phi(y) = \frac{1}{\mu}\int_0^y zf(z)dz$ is the Lorenz function. The four traditional welfare measures are:[2]

- 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: $1/2\mu \int_0^{\bar{y}} \left[yF(y) - \mu\phi(y)\right] f(y)dy$.
- The standard deviation of logarithms (SDL): $\int_0^{\bar{y}} [\log(y/\mu)]^2 f(y)dy$.

[2] Virtually the only other commonly used welfare measures are transformation of these four, such as the square of the coefficient of variation or the variance of the logarithms.

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. 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. 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. Therefore, the choice of different conventional inequality measures implicitly assumes different judgments about inequality and social welfare.

Thus, if we accept Dalton's criteria, we may prefer the standard deviation of logarithms to the other three measures. Atkinson (1970) shows that Dalton's concept is the same as that of a mean preserving spread. Atkinson notes that all these measures (and any concave social welfare function) have the property that they 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 a welfare measure (closely related to Theil's index and various entropy indexes) that we refer to as the "Atkinson index." The Atkinson index has three strengths.

First, the Atkinson index uses a single parameter to nest an entire family of welfare that varies 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. Atkinson also believed that the measure should be independent of the mean level of incomes (as are most conventional measures): If the distribution on income in one country were simply a scaled-up version of that in a second country, we should regard the two countries as having the same degree of inequality. Finally, Atkinson imposed constant (relative) inequality-aversion.

Third, the Atkinson index has a desirable 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:

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

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

$$I = 1 - \frac{y_{EDE}}{\mu}. \tag{1}$$

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,

$$L = \mu - y_{EDE} \tag{2}$$

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

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

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

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:[3]

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

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 $\varepsilon \to \infty$, transfers at the lowest end dominate. If ε = 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 ε=0 as a degenerate case and only look at ε that are strictly positive. Following Atkinson

[3] Atkinson's welfare function is of the form of the generalized entropy measure in Tsallis (1988). In the limit as $\varepsilon \to 1$, this generalized entropy measure collapse to the standard Shannon entropy measure or Theil measure of welfare.

(1970), we assume that ε lies within the range (0, 2.5].[4] 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. The family demographic information and income data are from the Current Population Survey (CPS) March Supplement. The macro variables are from the Bureau of Labor Statistics' website. The minimum wage data are obtained from the U.S. Bureau of Labor Statistics' *Monthly Labor Review*. Data on the welfare 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").

Income and Welfare Measures: The CPS's total income measure, which is "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.[5]

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

[4] In his empirical work, Atkinson only considers $\varepsilon \leq 2.5$, plots one of his diagrams between 1.0 and 2.5, and suggests as an example 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.

[5] Blackburn and Bloom (1991) pointed out that the after-transfer, pre-tax income essentially double-counts the contribution of transfers, reasoning that "...an economy that experiences no growth in factor income, but increases the amount of money (frictionlessly) transferred through the government (and therefore the rate of taxation in order to finance the increased transfers), will record an increase in average total family 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 income, and other tax characteristics for the March CPS.[6] 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.

The CPS records income at the individual, family, and household levels. We use the family income measure. Kuznets (1953) contended that an ideal income-recipient unit for income study should satisfy three criteria: identifiability, inclusiveness, and distinct independence. Because the family is the recipient unit for most public assistance programs, the family is a better recipient unit than an individual based on the inclusiveness criterion. By the distinct independence criterion, we prefer the family to the household because nonfamily members of a household may not have a close economic connection. 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 welfare 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

[6] 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.

Victorial-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.[7]

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

Government Policies: The government policy variables vary by state or over time or both.[8] The income tax rate, disability insurance, and EITC phaseout rate vary across states. The minimum wage and unemployment insurance (UI) vary across states and time. The public assistance programs, Supplemental Security Income (SSI), Aid for Families with Dependent Children/Temporary Assistance to Needy Families (AFDC/TANF), food stamps, disability insurance, and Earned Income Tax Credit (EITC), vary over time, and SSI, AFDC/TANF, and food stamps vary across states.

We use two 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. The tax rates were obtained from the Congressional Joint Committee on Taxation website.[9]

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[7] 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.

[8] We cannot include programs such as Social Security Income that do not vary across states or over time. Social Security Income has been automatically adjusted to keep pace with inflation since 1972 so that real Social Security Income is constant over time.

[9] 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

The state-specific data on the minimum wage and maximum weekly unemployment insurance benefits are 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 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 a single-parent, three-person family to be eligible for assistance.[10] The AFDC/TANF eligibility

top bracket. Although the Low Tax rate and the High Tax rate are set simultaneously, their correlation is -0.52.

[10] 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.

standard is used for both that program and food stamps.[11] Our food stamps variable is the dollar value of the maximum monthly benefit. The 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.

To receive an EITC, a family must have reported 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. Beginning in middle 1980's, some states offered state EITC, usually in the form of a fixed percent of the federal EITC credit. The EITC benefit variable is adjusted by state supplements, hence this measure varies across both states and time. 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 is reduced by 15.98¢ for each extra dollar earned above $11,930 so that the benefit drops 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.

Macroeconomic and Demographic Variables: We include two macroeconomic variables to control for economic conditions. The gross domestic product (GDP)[12] and state unemployment rates are from the Bureau of Labor Statistics' website. In addition to state dummy variables, we include state-level demographic characteristics obtained from the CPS: the

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

[12] We use national rather than state-level GDP to avoid circularity. We experimented by replacing the GDP with the gross state products and obtained very similar results.

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 government variables in thousands of dollars.

Regression Model

Unlike most previous welfare or income distribution studies that examine the effect of a single government program, we control for all the major government programs that directly or indirectly transfer income to the poorest members of society (and that vary in real terms cross-sectionally or over time 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 family's transferred income because other government transfer programs are contingent on income.

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 obtained 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 appropriate value of ε, we could use I_ε to proxy the inequality ranking from the traditional inequality indexes. Nonetheless, we conduct our analyses using all the welfare measures.

Using observations for state *i* in year *t*, we regress our various welfare 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}:

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

where ζ_{it} is the error term. We cannot include year dummies because some policy regressors are invariant across states and hence change only over time.

We estimate this fixed-effect model using least squares allowing for panel specific first-order autoregressive errors. We report White's heteroskedasticity-consistent standard errors corrected for the panel structure, where the disturbances are assumed to be heteroskedastic and contemporaneously correlated across panels (Beck and Katz 1995).

The Atkinson and Gini indices are constrained to lie between 0 and 1, where 1 reflects complete inequality.[13] All the inequality measures are measures of the distance between the actual income distribution and one in which everyone has the same income (a uniform distribution). All these measures are nonnegative, and an increase in any of these measures is supposed to reflect an increase in inequality. Consequently, for all welfare measures, a positive coefficient indicates that an increase in the corresponding variable reduces welfare or equality, while a negative coefficient indicates that the variable has an equalizing effect.

[13] 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.

We regressed each of the pre-tax and post-tax welfare 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 is obtained by adding 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: The regression results for the traditional inequality measures and several Atkinson measures are reported 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 well: The R^2 measures range from 0.88 to 0.99.

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 near 0, and 2.5 at 0.25 increments.[14] 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

[14] 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 $\partial I_\varepsilon / \partial p_i$.

across welfare measures (values of ε). [To save space, we do not show the statistically insignificant elasticities for the three AFDC/TANF variables.]

Taxes: Raising the marginal tax rates increases after-tax equity. As Table 1 shows, an increase in either marginal tax rate, "High Tax" and "Low Tax" statistically significantly increases welfare the coefficients are negative — 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 low marginal tax rate has a greater welfare-increasing effect the larger is ε (the more weight the Atkinson measure places on the least well-off measures of society). For the high marginal tax rate, the welfare-increasing effect is greatest for low values of ε (and virtually the same for all ε greater than 1).

Increasing the Earned Income Tax Credit benefit raises after-tax welfare. The coefficient for our EITC maximum benefit variable (the product of the credit rate and the income threshold for the maximum benefit) is statistically significantly negative for the four traditional measures and the Atkinson measures for $\varepsilon \leq 1.75$. Unlike the AFDC/TANF and Food Stamps programs, the EITC may have desirable incentive effects. Eissa and Liebman (1996) and Meyer and Rosenbaum (2000) show that the EITC increased the labor supply of single mothers.

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. The behavioral effects of lowering the phaseout rate are theoretically ambiguous. A lower phaseout rate reduces the work disincentive for those already in the program but raises the break-even point (the top end of the phaseout range), drawing more recipients onto the rolls and therefore reducing their labor supply. For example, Eissa and Hoynes (1998), who model the labor supply of couples jointly, found that the EITC reduces the amount of labor that wives supply. Unambiguously as the phaseout rate rises, current recipients receive less income. Some original recipients with income close to the break-even point will no longer be eligible since the break-even point is lowered, while other recipients remained in the programs will reduce their labor supply due to the increased work disincentive. Consequently, we may observe increased inequality since the reduction in income received is concentrated at the low income families.

Minimum Wage: Although Congress reputedly passed the minimum wage legislation to help the working poor, it fails to do so. The minimum wage coefficient is statistically significantly positive — lowers pre-tax welfare — for all welfare measures (not shown in Table 2). For the after-tax welfare 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, Couch and Wittenburg (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, Schweitzer and Wascher (2000) suggests 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.[15]

Social Insurance Programs: The social insurance programs have differing effects. Unemployment insurance has a statistically significant at the 10% level disequalizing effect on Atkinson index with $\varepsilon \geq 2$ (where we heavily weight the low end of the income distribution). 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 increases welfare 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) increases welfare 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 welfare 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 reviewed by Moffitt (1992) unequivocally show that the AFDC program generates a nontrivial work disincentive. The

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[15] The reduction in real minimum wage may contribute to the rise of wage dispersion in the lower portion of wage distribution (see DiNardo, Fortin and Lemieux 1996, Lee 1999 and Teulings 2001).

AFDC benefit levels are about the same as a woman would receive if she works full-year full-time in a minimum-wage job. 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 welfare 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 $I_{2.5}$.[16] The larger the share of female-headed families, the less equal is the income distribution. This result is consistent with the literature (e.g., Gottschalk and Danziger

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

1993) that the change of family structure, especially the dramatic increase of female-headed family, substantially contributed to the surge 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 welfare equation on six regional dummies. For the traditional measures and the Atkinson indexes for $\varepsilon < 2$, 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 ran a series of experiments with alternative estimation methods and another series with different model specifications (available from the authors). The explanatory variables are highly multicollinear because the real value of the variables and the demographic characteristics change only slowly over time. The condition number is 553 for all the regressors and 152 for all the regressor except the state dummies.[17] Because these condition numbers are well above 20, we have a collinearity problem (Greene 1997). Consequently, we estimated our model using the generalized maximum entropy (GME) method of Golan, Judge and Miller (1996) and obtained virtually identical results. GME is a robust technique that works well with ill-conditioned problems. We further modify the general linear model to allow for first-order autoregressive errors (Golan , Judge and Miller 1996,

[17] If $\mathbf{X}$ is the matrix of the right-hand-side variables where we have scaled each column so that it has unit length, then the condition number is the square root ratio of the largest to smallest characteristic root of $\mathbf{X}'\mathbf{X}$.

Section 9.2). The GME estimates are virtually the same as to OLS estimates but tend to be smaller in absolute value (which should be expected with a shrinkage estimator like GME).

Because some key policies vary over time but not across states, we are not able to estimate fixed-year effects. Instead, we estimated a mixed-effects model, treating the state effects as fixed effects and year effects as random effects. We used maximum likelihood because generalized least squares estimates, which requires initially estimating fixed-year effects to obtain the estimates for errors, is infeasible due to the perfect correlation between year dummies and some explanatory variables. The estimates with random year effects and those without random year effects are close. The only notable difference is that the effects of the EITC benefits are not statistically significant in the random-effect model. Moreover, the hypotheses of random year effects are rejected 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 weighted each adult the same when calculating our welfare measures. An alternative approach would be to calculate these measures using the CPS family weights, which reflect how many similar families there are in the general population.[18]

The correlation coefficient between the weighted and the unweighted Atkinson indexes is 0.91 on average and the estimated coefficients from the weighted and unweighted version are identical to two digits after the decimal point.

Second, we normalized 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

[18] We chose not to use the CPS family weights because they are designed to produce accurate estimates for calculations involving the entire country rather than for individual states.

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.

Third, we control for macroeconomic variables, aggregate demographic variables and state dummies. To examine how our results are affected by including these additional variables, we conducted 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 remained 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 were virtually the same as in our full regression.

Finally, 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.

Magnitude of Policy Effects

So far, we have shown that the directions of policies' welfare effects are generally consistent across welfare 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.

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 ε= 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 by 10% the 1997 level of the Low Tax rate, 15% to 16.5%, the Atkinson index changes to $\widehat{I}'_\varepsilon = \hat{I}_\varepsilon + 0.165 \times \widehat{\beta}_{\text{Low Tax}}$, where $\hat{I}_\varepsilon$ is the estimated actual Atkinson index for 1997 family income and $\widehat{\beta}_{\text{Low Tax}}$ is the estimated coefficients 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))[19]

$$\Delta L = \left(\mu_{97} - \hat{y}_{EDE}\right) - \left(\mu_{97} - \hat{y}'_{EDE}\right) = \mu_{97}\left(\hat{I}_\varepsilon - \hat{I}'_\varepsilon\right)$$

where μ_{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.[20] 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.

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

[20] 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.

The welfare effects of policy changes for $\varepsilon \neq 1$ can be calculated in the similar fashion. The results are reported in Table 3. Among the welfare improvement which are significantly different from zero, when $\varepsilon = 2.5$, Low Tax has the biggest equalizing effect and minimum wage has the biggest disequalizing effect. The welfare effects of other policy changes for various values of ε are reported in Table 3. For example, the table 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 $\varepsilon = 1$.

Semi-Parametric Estimates

So far, we have relied on parametric regression models. We examined how sensitive our results are to changes in the estimation method and the specification (including the choice of welfare measure). Alternatively, we can use a semi-parametric approach to examine the impact of policies on the entire income distribution.

DiNardo, Fortin and Lemieux (1996) use semi-parametric approaches to examine the impact of labor market structure and the minimum wage on wage distribution. They estimate the effects of various labor market factors by applying kernel density methods to appropriately weighted samples. Under the assumption that the factor of interest has no general equilibrium effect, the reweighted density is the counterfactual density. Hence, the difference between the counterfactual density and original density captures the effects of the particular factor on the distribution. Because many factors change between two points of time, DiNardo, Fortin and Lemieux (1996) proposed a sequential decomposition procedure, which accounts for the change of various factors sequentially using the reweighting technique. However, the results obtained in this fashion are not invariant to the order of this sequential process. Alternatively in their study of the distributional effects of the minimum wage, Neumark, Schweitzer and Wascher (1998) apply this reweighting technique to "difference-in-difference" estimates to account for change of other factors.

We use an alternative method where we estimate a closed-form maximum entropy (maxent) density function semiparametrically. According to the maximum entropy principle, out of infinite numbers of distributions that satisfy known moment conditions, we should choose the one that maximizes Shannon's information entropy (Jaynes 1957). The maxent density is the `most uncommitted' and most conservative density in the sense that we express maximum uncertainty about the information that is not implied by the known moment conditions. In other words, out of all possible densities satisfying these moments, the maxent density is the closest one to the uniform distribution. Zellner and Highfield (1988) and Wu (2001) discuss the methodology for calculating the maxent density subject to known moment constraints. Golan, Judge and Perloff (1996) use discrete entropy and LaFrance (1999) use continuous entropy to estimate densities in their empirical works.

We obtain an estimate of the maximum entropy density by maximizing Shannon's information entropy measure, $-\int f(y)\log f(y)\,dy$, subject to i moment conditions,

$$\int g_i(y) f(y)\,dy = \mu_i ,$$

where $\mu_0 = 1$ to guarantee that the density integrates to one. We can solve the maximization of entropy problem using the Lagrange method. The solution takes the form $f(y) = \exp\left(-\sum \lambda_i \mu_i\right)$, where the λ_i's are the Lagrange multipliers. The moments μ_i's are the sufficient statistics of the exponential distribution $f(y)$. Since an analytical solution is generally not available, we solve this nonlinear optimization problem using Newton's method iteratively.

This maximum entropy estimator is equivalent to maximum likelihood estimator, consistent and efficient.[21]

Generally, the impacts of change in a single moment, except for the first two arithmetic moments, on the shape of the density function of a non-normal distribution are difficult to predict a priori. It is even more difficult to predict the impacts of changes in multiple moment conditions. We examine these relationships directly by examining how policies affect moments and how moments subsequently determine the density.

We use a two-step approach. First, we learn how policies affect the moments by regressing the sample moments, $\boldsymbol{\mu}$, on the policies and other control variables. Second, we use the estimated relationship between the policies and the moments to predict how a policy change affects the moments. Then we calculate a counterfactual density by fitting the predicted moments to a maxent density.

Using a parametric regression as the first step in our approach frees us from the restrictive assumptions about the conditional distribution involved in the reweighting methods. The change of other factors other than the factor of interests is accounted for in the parametric multiple regressor regression in the first step. Consequently, we are able to isolate the effects of change in a particular policy from all other confounding factors using our two-step approach.

Employing the maximum entropy method and using the first six moments, we apply the proposed approach to analyze the effects of changes in some key policies on 1997 family

[21] This maximum entropy method is equivalent to the ML approach where the likelihood is defined over the exponential distribution with six parameters. Golan, Judge and Miller (1996) use a duality theorem to show this relationship.

income. We have found that we can approximate the 1997 family income distribution very well using the following density function[22]

$$f(y) = \exp\left[-\lambda_0 - \sum_{i=1}^{6} \lambda_i \log^i(y)\right], \tag{5}$$

where

$$\lambda_0 = \log \int_0^\infty \exp\left[-\sum_{i=1}^{6} \lambda_i \log^i(y)\right]$$

is a normalization factor which guarantees that the density integrates to one. The exponential functional form of Equation (5) is highly flexible and nests the Pareto, lognormal, and generalized lognormal distributions as special cases. We plot the estimated maxent density (imposed on the histogram) for 1997 family income in Figure 2. One can see that we are able to recover the general shape of the income distribution by using the information contained in the first 6 moments.

To check the goodness of fit of our estimated density, we calculate the Kolmogorov-Smirnov statistic (0.0046).[23] The 5% critical value for the Kolmogorov-Smirnov test is 0.0052 for our sample. Hence we do not reject the hypothesis that the income sample is distributed according to the distribution (5). The top two rows of Table 5 compare various calculated welfare measures for the actual sample to those calculated from the estimated density. All of these pairs of

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[22] Teulings (2001) uses similar function form to approximate wage distribution in his works on minimum wage's effects on wage distribution and return to human capital.

[23] Given N observations $[y_1, y_2, \ldots, y_N]$, we define the empirical distribution function as $E_i = n(i)/N$, where $n(i)$ is the number of observations smaller than y_i. The two-sided Kolmogorov-Smirnov test is

$$KS = \max_{1 \le i \le N} |F(y_i) - E_i|,$$

where $F(y_i)$ is the theoretical cumulative density function of the distribution being tested, which must be continuous and fully specified.

measures are identical to two or three decimal places, which suggests the estimated density fits the income sample extremely well.

We regress the six moments for the 1997 family income used in Equation (5) on the same set of regressors as in Equation (4).[24] Table 4 shows the estimated regression coefficients for each moment for just the policy variables to save space. Only the AFDC/TANF Need, TANF Reform, Disability Insurance, and Food Stamps variables have a statistically significant effect on the mean of income. Many of the other policies — particularly the taxes, the minimum wage, SSI, and AFDC/TANF Need — affect the higher order moments and thereby the shape of the entire income distribution.

We then use our estimates from the moment equations to simulate how a change in one policy affects the entire distribution. For example, suppose the Low Tax rate increases by a fourth. The new counterfactual moments are

$$\hat{\boldsymbol{\mu}}' = \hat{\boldsymbol{\mu}} + \hat{\beta}_{\text{Low Tax}} \times 25\% \times 15\%,$$

where $\hat{\boldsymbol{\mu}}$ is the vector of sample moments, $\hat{\beta}_{\text{Low Tax}}$ is the corresponding vector of estimated coefficients of the low marginal tax rate, 25% is the hypothetical increase in that tax rate, and 15% is the actual marginal tax rate for the lowest bracket in 1997. Next, we calculate the counterfactual maxent density, Equation (5), using the counterfactual $\hat{\boldsymbol{\mu}}'$.

In Figure 2, we show the effects on the income distribution from a 25% increase in the Low Tax rate, Minimum Wage, the EITC Benefit, or the EITC Phaseout rate by plotting the difference in the counterfactual and actual densities. The increases in the Low Tax rate or EITC Benefits cause a drop in the density at the lowest end of the distribution, an increase in the next

[24] We deflated income using the Consumer Price Index. In Table 4, the higher-order moments are based on a sample that was normalized by dividing by the first moment.

lowest segment, a small reduction in the following segment, and virtually no effect at the high end of the income distribution (over $100,000). An increase in the minimum wage or the EITC Phaseout Rate has the mirror effect: a rise, a drop, a small rise, and then no effect across income groups. Neumark, Schweitzer and Wascher (1998) examined the effects of minimum wage on family income distribution using a non-parametric approach. They concluded "…the overall effects are to increase the proportion of families that are poor and near-poor, and to decrease the proportion of families with incomes between 1.5 and 3 times the poverty level." One can see from Figure 3 that our results about minimum wage are completely consistent with their finding.

The last section of Table 5 shows how these policy experiments would change various welfare measures. For each policy, the first row shows the percentage change in the welfare measure based on the semi-parametric analysis and the second row shows the corresponding changes based on our earlier parametric estimates. By comparing these pairs of rows, we find that both methods produce qualitative identical and quantitatively close results. Again, we find that an increase in Low Tax or the EITC Benefit level raises welfare (has a negative effect on the welfare indexes), and an increase in the minimum wage or the EITC Phaseout rate reduces welfare. The welfare effects from changing the other policies are also close for the semi-parametric and parametric estimates.

Conclusion

What can the government do to raise welfare by achieving a more equitable income distribution? To answer this question, we examine the effects of the major government social insurance and redistribution policies on all the commonly used welfare 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. We draw four main conclusions.

First, it is practical to study the welfare effects of government programs because almost all the estimated results are qualitatively identical across common welfare measures. Moreover, we find that the results are nearly identical for both parametric and semi-parametric analyses.

Second, an effective way to desirably redistribute income is to use taxes. The marginal tax rates have larger and more desirable 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 welfare 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 effect on welfare, 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 incomes has little effect on the Atkinson index if $\varepsilon < 1$; but, if $\varepsilon > 1$, has a substantial effect 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 systematically "trim" the data 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,

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

where $\boldsymbol{y}$ is the income vector with $\boldsymbol{w}$ 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 is 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 "Min." 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 ("Max." column) was 43 in California in 1992 (out of 6,164 families). Compared to some common practice employed in traditional studies, such as remove the families with income below the first percentile or some arbitrarily chose 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

	Min.	*1st Quar.*	*Median*	*Mean*	*3rd Quar.*	*Max.*
Value of truncating point	50	50	185	211	300	1213
Number of families dropped	1	1	2	3	4	43
Percent of families dropped	0.04	0.14	0.21	0.29	0.37	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

Variables	*Unit*	*Mean*	*Std. Var*	*Min.*	*Max.*
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 dollar/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 dollar/week	0.19	0.08	0.06	0.72
SSI	1,000 dollar/month	0.32	0.05	0.26	0.63
Disability Insurance	1,000 dollar/year	0.31	0.04	0.24	0.38
AFDC/TANF	1,000 dollar/month	0.29	0.12	0.08	0.68
AFDC/TANF Need	1,000 dollar	0.43	0.15	0.17	1.30
Food Stamps	1,000 dollar/month	0.18	0.03	0.09	0.30
GDP	1,000 billion dollar	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
(t-statistics below the coefficient)

	GINI	*COV*	*RMD*	*SDL*	$I_{0.1}$	$I_{0.5}$	I_1	$I_{1.5}$	I_2	$I_{2.5}$
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 >= 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 of dollars) for 10% Increase in Policy Levels

	$I_{0.1}$	$I_{0.5}$	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 significant different from zero at 5% level.
* Statistically significant different from zero at 10% level.

Table 4: Regression Results for Policy Variables on the First Six Moments of Log. Income

	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6
Low Tax	0.15	-1.34**	3.02**	-10.38**	41.86**	-188.5**
High Tax	0.01	-0.18**	0.31**	-1.16**	3.86*	-16.77*
Min. Wage	0.01	0.04**	-0.12**	0.58**	-3.28**	16.06**
Unemployment Insur.	-0.01	0.03	-0.09	0.56	-2.19	11.20*
SSI	-0.01	-0.08	0.65**	-3.85**	18.72**	-95.87**
AFDC/TANF	0.03	0.04	-0.28	1.06	-2.94	9.48
AFDC/TANF Need	-0.04**	0.04*	-0.14**	0.70**	-3.78**	20.53**
AFDC Reform	0.02**	-0.02*	0.06*	-0.23*	1.02**	-4.39*
Disability Insurance	-0.24**	-0.11*	-0.04	0.03	0.52	-9.42
Food Stamp	-0.53**	0.43**	-0.92*	2.07	-5.21	8.73
EITC Benefit	-0.01	-0.04**	0.02	-0.20	0.38	-1.42
EITC Phaseout Rate	-0.11	0.71**	-0.40	4.27**	-6.90	44.92

** Statistically significant different from zero at 5% level.
* Statistically significant different from zero at 10% level.

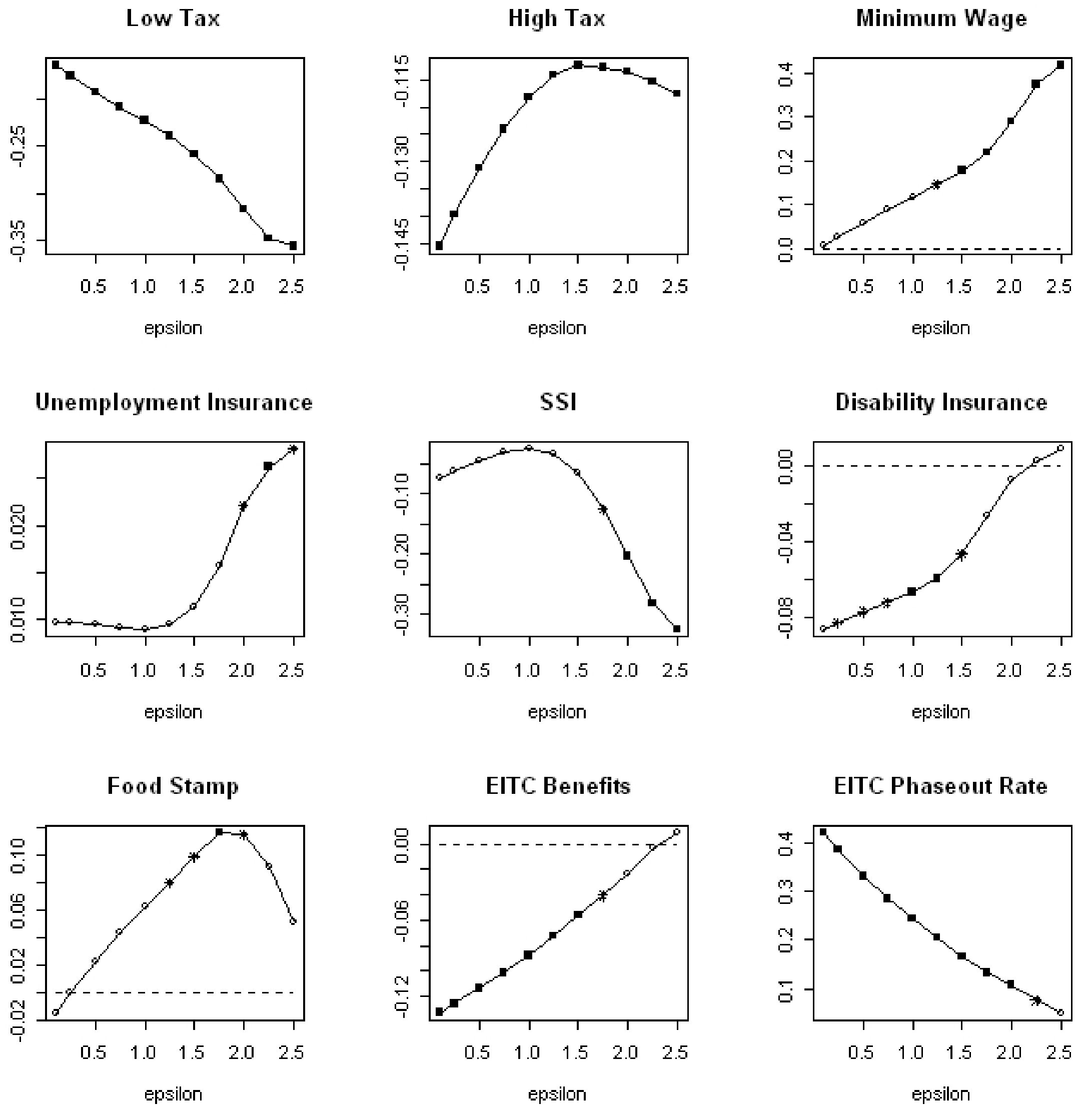
Note: Coefficients on non-policy variables are available from the authors.

Table 5: Welfare Indexes Estimates and Percentage Change for 25% Change in Policy Levels

	GINI	$I_{0.1}$	$I_{0.5}$	I_{1}	$I_{1.5}$	I_{2}	$I_{2.5}$
Estimated Welfare Indexes							
Actual Sample	0.372	0.025	0.118	0.227	0.340	0.476	0.644
Estimated Density	0.374	0.025	0.118	0.227	0.340	0.475	0.640
Percentage Change of Welfare Index for 25% Change in Policy Levels							
Low Tax	-2.29	-2.82	-4.00	-5.23	-6.31	-7.75	-9.30
	-2.52**	-3.52**	-4.33**	-5.25**	-6.27**	-7.74**	-8.61**
Min.	1.54	-0.87	1.04	2.39	3.83	7.14	10.03
Wage	0.56	0.09	1.18	2.49	3.85**	6.36**	9.12**
EITC	-1.87	-4.27	-3.70	-3.03	-2.42	-1.91	-1.51
Benefit	-2.09**	-4.27**	-3.82**	-3.09**	-2.04**	-0.87	0.34
EITC	4.58	12.41	10.15	8.01	6.35	4.84	3.15
Phaseout Rate	5.12**	12.54**	10.32**	7.94**	5.57**	3.63**	1.67

Note: For each policy variable, the first row is the percentage change predicted by the semi-parametric analysis and the second row by the parametric analysis.

Figure 1: Estimated Elasticities of Atkinson Index with 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.

Figure 2: Histogram of 1997 Family Income and Estimated Maxent Density

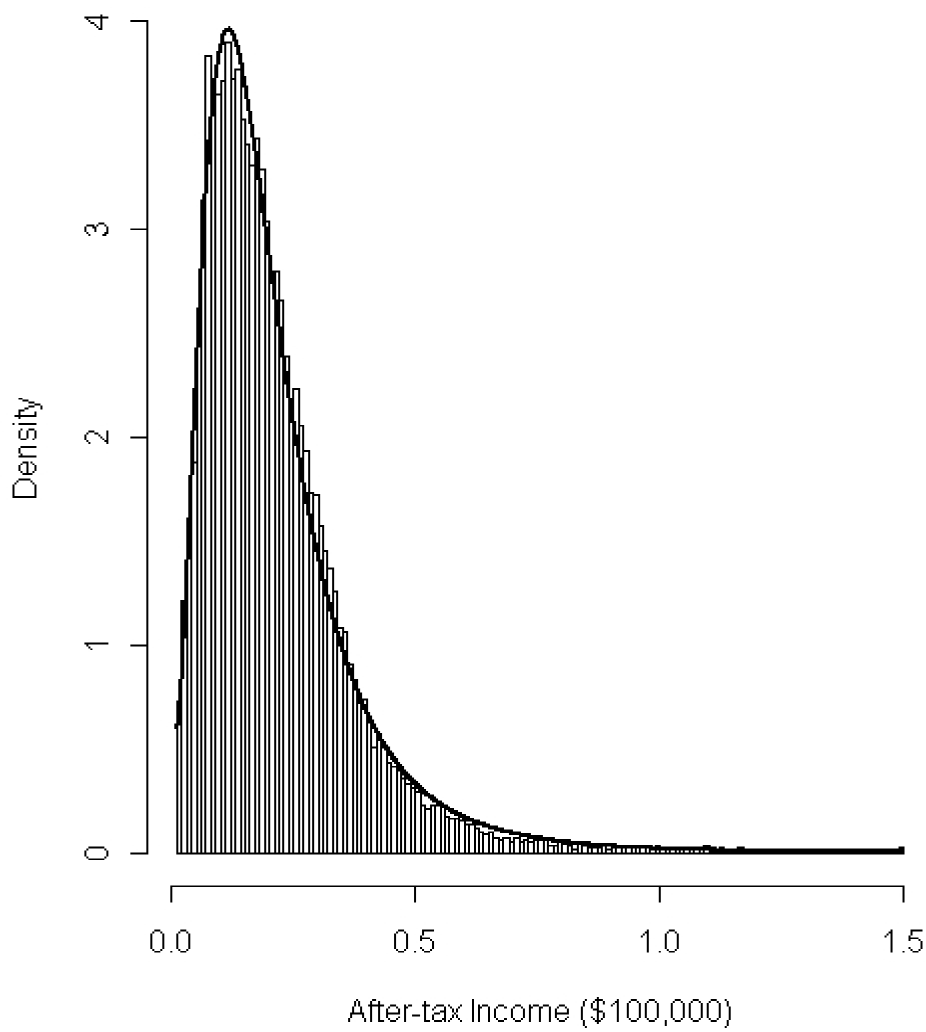
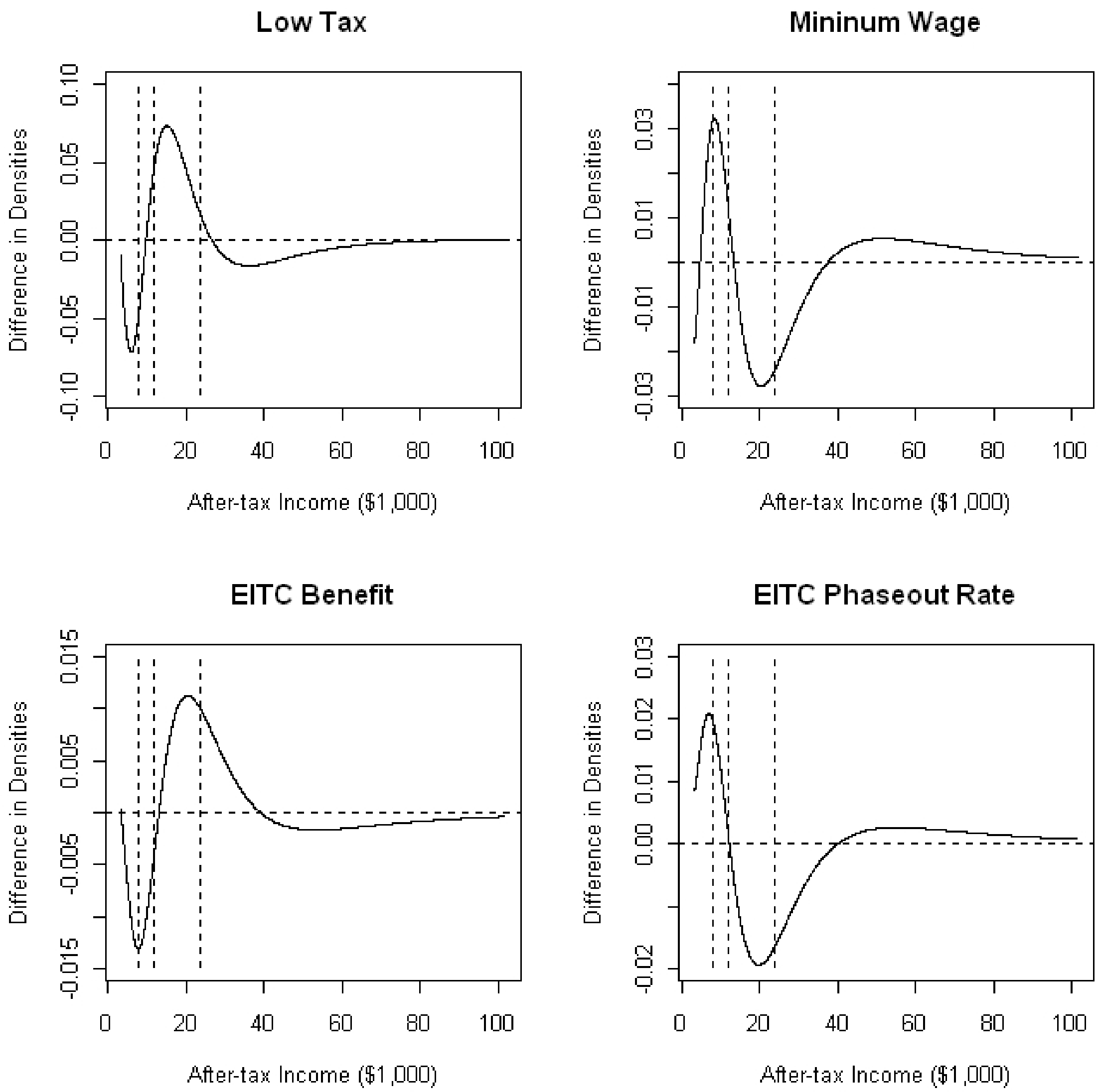


Figure 3: Difference in Densities: Counterfactual Density for 25% Increase in Policy Level — Actual Density



Note: The first vertical line is 1997 poverty line ($7,890); the second line is 1.5 times the poverty line; the third is 3 times the poverty line.