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Abstract

The minimum wage, unlike most government transfer programs, lowered welfare in the 1980s and 1990s as measured by all commonly used welfare or inequality measures, including various Atkinson indexes, the Gini index, standard deviation of logarithms, and others. The effects of most government programs, macroeconomic variables, and aggregate demographic characteristics were qualitatively the same for all the inequality measures.

Do government programs such as minimum wage laws, Aid to the Families with Dependent Children/Temporary Assistance to Needy Families, Food Stamps, Unemployment Insurance, Earned Income Tax Credit, and Supplemental Security Income raise welfare by redistributing income? At first glance, 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 for almost all the policies.[1] Moreover, we demonstrate that the minimum wage – in contrast to most government transfer programs – lowers welfare.

We use all the common, traditional welfare measures: Gini index, coefficient of variation of income, relative mean deviation of income, and standard deviation of the logarithm of income. We also use the Atkinson welfare index, which has four desirable properties. First, the Atkinson welfare index has a dollar-denominated interpretation. Second, the measure for the entire population can be decomposed into within-groups and between-groups welfare measures for subgroups of the population. Third, changing the single parameter that indexes the Atkinson measure changes the weight the welfare index places on relative increases of wealth at the lower end of the income distribution. Thus, by varying this parameter, we can examine the effects of government policies over a range of social welfare functions. Fourth, the Atkinson measure can be derived axiomatically to be consistent with a welfare maximization model.

We examine how differences in government policies and macro and demographic variables over time and across the fifty states affect welfare. Though we evaluate seven government policies, we emphasize the welfare effects of the minimum wage. Most of the enormous

[1] Dalton (1920) suggested that all common welfare measures would give the same rankings "in most practical cases." However, Yntema (1933), Ranadive (1965), and Atkinson (1970) show that they give different rankings. Instead, we show that, empirically, changes in government policies (and macroeconomic and aggregate demographic variables) change the rankings of almost all measures in the same direction.

body of research on the minimum wage as well as the majority of public debates have focused on its unintended employment effects and its effects on wages rather than as its role in redistributing income.

Relatively few studies have looked at its effects on the income distribution. Unlike this study, most of these earlier studies have not controlled for the effects of other government policies and market conditions when evaluating the effects of the minimum wage laws. 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 results in different settings." Moreover, earlier studies of the income effects of the minimum wage laws have not taken the next step of using a welfare measure to ascertain whether the minimum wage 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 minimum wage's effects on the entire income distribution.

All of our welfare indexes measure relative incomes. Each is normalized by the mean of the distribution. By also examining the impact of policies on the first four moments of the income distribution, we can examine the effects on the level of income and the shape of the income distribution.

We also investigate the effects of government programs on two population subgroups: those households headed by people with at least a high school education and those with less than a high school education. We find that the minimum wage exacerbates both the within-group inequality of each subgroup and the between-group inequality.

Literature Review

The minimum wage literature is enormous. Card and Krueger (1995) reviewed earlier studies and Neumark, et al. (2000) discussed more recent works. Most studies focused on the minimum wage's effects on employment or wage. Nearly all empirical studies (e.g., Neumark and Wascher 1992, 2000; Currie and Fallick 1996; Abowd et al. 1999; and Neumark et al. 2000), find that the minimum wage reduces employment; however, Card and Krueger (1994, 1995, 2000) report that a moderate increase in fast-food employment followed New Jersey's 1991 minimum wage hike.[2]

The literature's view on wage effects is also mixed. Card and Krueger (1995) and DiNardo et al. (1996) find that increasing the minimum wage raises low-wage workers' wages and has some effect on workers with wages just above the minimum, so as to compress the wage distribution. DiNardo et al. (1996) and Lee (1999) found that a drop in the real minimum wage significantly raised wage inequality during the 1980's. In contrast, Neumark et al. (1998) concluded that net effect of the minimum wage law on wages is much smaller if one takes into account the lagged effect, which turns out to be strongly negative. Although virtually all studies find that the minimum wage raises the average wage in the nonfarm sector, Moretti and Perloff (1999) observed that increases in the minimum wage lowers some agricultural wages.

Because an increase in the minimum wage may affect wages, participation rates, and hours worked (Neumark et al. 1998), a recent trend in minimum wage studies has been to use labor income as an overall measure of economic well-being at the individual level.

[2] Rebitzer and Taylor (1995) and Carter (1998) showed theoretically that a minimum wage can increase employment in an efficiency wage model (for reasons similar to those with a monopsony). Drazen (1986) and Perri (1990) show that the minimum wage can lower employment but be Pareto-improving in an efficiency wage model. Lang and Kahn (1998) reach a similar result using a model of bilateral search with heterogeneous workers.

In addition, a minimum-wage induced increase in earned income of the working poor may reduce the government transfers they receive. Thus, we use a measure of total family income that includes monetary government transfers so that we can investigate the distributional effects of the minimum wage and other government programs.

Several studies (e.g., Gramlich 1976, Johnson and Browning 1983, Burkhauser and Finegan 1989, and Horrigan and Mincy 1993) examined the redistributive effects of minimum wages by simulating the redistribution of family income under some restrictive assumption about employment and other effects. For example, Johnson and Browning (1983) noted that, even if they assume no disemployment effect from a minimum wage, it has at best a very small desirable impact on income distribution. However, because there is no agreement on magnitude or sign of the employment elasticity nor is there consensus on how the minimum wage influences the distribution of family income through other factors, these studies offer only limited insight into redistribution effects.

Some recent studies present "before and after" analyses to determine how the minimum wage affects wage or income distributions. Card and Krueger (1995) estimated the effects of 1989-1991 federal minimum wage rise on the distribution of family income across states. They divided the population age 16 and older into 10 equal-sized groups based on their weekly family income normalized by number of earners in the family. By comparing the change of family income percentiles before and after the minimum wage hike, they found that the 1989-1991 federal minimum wage increase significantly benefitted the poorest decile relative to the richest decile, especially in the states with many minimum wage workers. They concluded that the minimum wage substantially compresses the income distribution. According to their calculation, more than one third of the earnings gain from the minimum wage hike goes to the families in the lowest family income decile.[3]

[3]Under the assumptions of no employment and no "ripple" effects, an increase in the minimum wage must

Burkhauser et al. (1996) modified Card and Krueger's distributive analysis, grouping the population by relative family income rather than by family income deciles. They contended that the ratio of family income to the poverty level, which controls for the family's demographic characteristics, is a more appropriate measure of family economic well-being than Card and Krueger's decile comparison. They found that the minimum wage workers are evenly distributed across family income groups, which is consistent with the findings of Horrigan and Mincy (1993), O'Brien-Strain and MaCurdy (2000), and our findings. They concluded that the minimum wage is very ineffective in helping the working poor, even if it involves only very small negative employment effect, and that the net effect could be negative under some circumstances.

O'Brien-Strain and MaCurdy (2000) drew a similar conclusion. Using the California data from the Survey of Income and Program Participation (SIPP) and the Consumer Expenditure Survey (CES), they estimated the costs and benefits of the 1996 federal minimum wage increase and the distributional effects. They found that high-income families and low-income families are nearly equally likely to benefit from the minimum wage. On the other hand, 22% of the additional earnings goes to taxes. Under the assumption that all the costs from the higher minimum wage are passed through as higher prices, low-income families face a larger percent increase in the price of the goods they purchase. Consequently, the net effect of raising the minimum wage is negative averaging across all families.

Neumark et al. (1997) reported that the minimum wage's net effects on poverty more closely resembles "income redistribution among low-income families than income redistribution from high to low-income families." A minimum wage hike may relatively reduce income of poor families because the disemployment effect is concentrated among low-income

narrow the income gap between low-wage and high-wage workers. However, under the same assumptions, Burkhauser and Finegan (1989) found that the poor received less than 12% of the additional gains from the 1984 minimum wage hike while 39% went to families with income at least three times the poverty line.

families.

Neumark et al. (1998) used those states that raised the minimum wage as the treatment group and the other states as the control group. Their key endogenous variable is the ratio of income to the government's poverty level. They examined the difference between this variable's level for the treatment group and the control group before and after changes in the minimum wage levels (a nonparametric "difference-in-difference" approach). They reported that, although the minimum wage raises incomes of some poor families relative to the poverty level, overall it increases the proportion of poor and near-poor families and decreases the proportion of families with incomes just above the poverty line. Thus, they concluded that the minimum wage lowers both efficiency and equity.

Neumark et al. (2000) examined how an increase in the minimum wage affects wages, hours, and employment. They considered the possibility that the minimum wage works with a (one-year) lag. They concluded that the combined current and lagged wage, hours, and employment effects lead to a decline in earned income for low-wage workers.

Welfare Measures

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, $\bar{y}$ 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:[4]

[4] 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.

- **The coefficient of variation**: V/μ.

- **The relative mean deviation**: $\int_0^{\bar{y}} \; |y/\mu - 1| \, f(y) \, dy$.

- **The Gini index**: $1/2\mu \int_0^{\bar{y}} [yF(y) - \mu\phi(y)] f(y) dy$.

- **The standard deviation of logarithms**: $\int_0^{\bar{y}} \; [\log(y/\mu)]^2 f(y) dy$.

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.

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 that we call the "Atkinson index."[5] The Atkinson index has four strengths. We discuss three of these now, and the decomposability

[5] Closely related indexes are often referred to as entropy measures or Theil's index.

property in the last substantive section.

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 1980a, 1980b; Cowell and Kuga 1981a, 1981b). 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:

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

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,* L, from inequality,

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

is a transformation of 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 algebra manipulation using Equations 1 and 2, Atkinson obtained his welfare index for n people:[6]

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

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 $\varepsilon = 0$, the utility function is linear

[6] 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.

in income and the distribution of income does not affect the welfare index: $I_0 = 0$ 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].[7] In our empirical work, our lowest value is $\epsilon = 0.1$.

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.

We use the CPS's total income measure, which is "the amount of money income received in the preceding calendar year" including in-cash government transfers but not food stamps and other in-kind government transfers. This measure is gross of income tax payments, union dues, and Medicare deductions.[8]

The CPS records income at the individual, family, and household levels. We use the family income measure. Kuznets (1976) contends 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 over the household because nonfamily members of a household may not have a close economic connection. To adjust for family income

[7] In his empirical work, Atkinson only considers ε of 2.5 or less, plots one of his diagrams between 1.0 and 2.5, and suggests as an example that we might all agree that ε lies between 1.5 and 2.0. We experimented with larger values of ε, but found that larger ε put so much weight on the well-being of the poorest members of society that the welfare losses from any inequality virtually equal to all of society's income.

[8] Using this income measure that excludes noncash, we find substantial growth of inequality over time. According to Madden (2000), including noncash income is not likely to show less growth in inequality (see also Cutler and Katz 1992).

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 when $\varepsilon > 1$ 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 have little effect on the index. Even though there are few such families in the sample (0.3% of each state in a given year on average), we dealt with this sensitivity problem using a "trimming" method, which we discuss in the appendix.

Over our entire sample, the average values of the Atkinson indexes are 0.02, 0.12, 0.23, 0.48, and 0.62 respectively for $\varepsilon = 0.1, 0.5, 1, 2,$ and 2.5. 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.

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.*

Our government program variables vary by state or over time or both.[9] 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

[9] 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.

insurance, and Earned Income Tax Credit (EITC), vary over time, and SSI, AFDC/TANF, and food stamps vary across states.

Our minimum wage variable is the larger of the federal or the 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.[10] 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 indicates in which year each state first 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. The AFDC/TANF eligibility 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.[12] Our Earned Income Tax Credit (EITC) variable is the maximum annual benefit. EITC credit is phased out over a range.[13] In 1997, the phaseout income range was ($11,930, $25,750) for a one-child family. The credit falls at a rate of 15.98% of earnings above $11,930 and goes

[10] For our observation period, almost all the states set the maximum coverage period at 26 weeks.

[11] All AFDC/TANF families are income-eligible for food stamps unless they live in a large household. More than 85% of AFDC families usually receive food stamps.

[12] To qualify for SSI payment, a person must meet age or blindness or some other type of disability standard and have an income below the federal maximum monthly SSI benefit. Thus, our benefit variable represents both the maximum benefit and the eligibility standard.

[13] In 13 states, the federal EITC is supplemented by state EITC programs. We did not include a variable for the state EITC programs because state income taxes account for a small share of the total income taxes paid and because we could not model these programs with only one or two variables.

to zero at \$25,750. Our EITC threshold variable is the bottom of the range.

We include two macroeconomic variables to control for national economic conditions. The gross domestic product (GDP) and national unemployment rates are from the Bureau of Labor Statistics' website.[14] In addition to state dummy variables, we include state-level demographic characteristics obtained from the CPS: percentage of families with at least one adult member with at least a high school degree, percentage of female-headed families, percentage of people 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.

Effects of Government Policies on Welfare

We control for virtually all major government programs that directly or indirectly transfer income to the poorest members of society unlike most previous welfare or income distribution studies that examine the effect of a single government program. These government transfer programs directly affect family income. The minimum wage, disability insurance, and unemployment insurance have both direct effects on low-wage workers' earned income and indirect effects on their family's income because other government transfer are contingent on income.

We examined the correlation of the traditional inequality measures and the various Atkinson indexes ranking over our 850 state-year observations. The correlation 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

[14] We use national rather than state-level GDP and unemployment rates so as to reduce circularity and endogenerity problems.

ranking from the traditional inequality indexes. Nonetheless, wherever possible, we conduct our analyses using all the welfare measures.

Regression Model

Using observations for state i in year t, we regress our various welfare indexes, W_{it}^{j} (j = coefficient of variation, relative mean deviation, Gini, standard deviation of logarithms, and the various Atkinson indexes), on state dummy variables (49 out of the 50 states), D_i, government policy variables, macroeconomic variables, and our seven state-level demographic variables, Z_{itn}:

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

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.

The explanatory variables are highly multicollinear because the real value of the variables and the demographic characteristics change only slowly through time. The condition number is 592 for all the regressors and 174 for all the regressor except the state dummies.[15] Because these condition numbers are well above 20, we have a collinearity problem (Greene 1997).

[15] 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 $\mathbf{X}'\mathbf{X}$.

Not surprisingly given this collinearity, many coefficients estimated by ordinary least squares are individually insignificant but collectively significant at standard levels.[16]

Consequently, we decided to estimate our model using a robust technique designed for ill-conditioned problems. One possible approach is ridge regression. Another is the generalized maximum entropy (GME) method of Golan, Judge, and Miller (1996).[17] Because both ridge and GME techniques produce similar results, we report only the GME results. We further modify the general linear model to allow for first-order autoregressive errors (Golan, Judge, and Miller 1996, Section 9.2). We use White's heteroskedasticity-consistent covariance approach to calculate standard errors.

Regression Results

We start by examining whether policies increase or decrease the various welfare measures. Table 2 summaries the GME estimates of Equation 4 for the traditional inequality measures and the Atkinson index for $\varepsilon = 0.1, 0.5, 1, 2, 2.5$. The equations fit surprisingly well. The R^2 ranges from 0.44 to 0.82, and are above 0.64 for all the welfare indexes except the Atkinson index where $\varepsilon = 2.5$. The R^2 for the traditional measures are 0.71 or greater.

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. The Atkinson and Gini indexes are constrained to lie between 0 and 1, where 1 indicates complete inequality. The other three measures reflect the distance between the actual income distribution and a uniform distribution, hence they are

[16] Using a F-test, we reject the null hypothesis at the 0.05 level that the policy coefficients are jointly zero for $\varepsilon \leq 2$.

[17] In our GME estimates, the supports for the coefficients and noise terms are $[-1, 0, 1]$. These estimates are identical up to two digits after the decimal to what we obtain if we use a broader support of $[-2, 0, 2]$. Similarly if we use a support of $[-1, -0.5, 0, 0.5, 1]$, our estimates are identical to the original support up to three digits past the decimal point.

all nonnegative and increase with inequality.

The coefficients of the policy variables for the Atkinson indexes are plotted against ε at 0.25 increments (connected by a smooth line) in Figure 1. The coefficient appears as a solid dot if it is statistically significantly different from zero at the 0.05 level, and otherwise is represented as a hollow circle.

In each regression, the coefficient on the minimum wage is statistically significantly positive. Thus, holding other policies and factors constant, an increase in the minimum wage reduces welfare. As Table 2 illustrate (and Figure 1 shows for the Atkinson indexes), the minimum wage coefficient increases with ε. The figure and table show that the sign of most of the policy coefficients are the same across all welfare indexes.

The only exception where the coefficients are statistically significantly different from zero at the 0.05 level is the EITC benefits. Only for the coefficient of variation and the Atkinson index when $\varepsilon = 0.1$ (where variations in the income distribution is virtually irrelevant to welfare) is the EITC coefficient statistically significantly positive. The EITC phaseout variable is strongly statistically significantly negative for all welfare measures.

Other than the minimum wage, only unemployment insurance (UI), food stamps, and the Earned Income Tax Credit (EITC) have any statistically significantly positive coefficients. All the UI coefficients are positive and most are statistically significant. Although unemployment insurance is not a welfare program, it benefits working people rather than the poorest members of society, hence it is not surprising that it decreases equality.

All the statistically significant food stamp (dollar value of in-kind food transfers) coefficients are positive. One possible explanation is that food stamps reduce monetary income equality by discouraging the poorest members of society from working (Moffitt 1992).

The disability insurance program substantially increases welfare accordingly to all measures. Supplemental Social Security Income does not have a statistically significant effect at the 0.05 level for any welfare measure.

A rise in the maximum AFDC/TANF payment increases equality. However, a change in the need level for this program does not have a statistically significant effect (possibly because it is difficult to capture the complex eligibility standards in a single variable). The dummy variable that reflects the TANF "reforms" to AFDC program has either a positive or statistically insignificant effect across welfare measures (Table 2). These programmatic refomrs lowered welfare for Atkinson indexes where $\varepsilon \leq 1$ and did not have a statistically significant effect for larger values of ε, where more weight is placed on transfers at the lower end of the income distribution.

The direction of the effects of the demographic and macroeconomic control variables varies little across the welfare measures. Increases in GDP and in the unemployment rate tend to lower equality. Increasing average education tends to raise equality. An increase in the fraction of the population that is 60 or older, a decrease in the share of female-headed families, or a reduction in average family size generally tends to equalize income.

We find a systematic pattern in the state dummy coefficients. We regressed the state dummies from each welfare equation on six regional dummies. For Atkinson indexes with ε less than 2 and the other welfare measures, two regions had statistically significantly higher coefficients (less equality) than for the other four regions. The largest regional effect is for the South Central region (Arkansas, Kansas, Louisiana, Missouri, Oklahoma, and Texas) followed by the South Eastern region (Alabama, Delaware, Florida, Georgia, Kentucky, Maryland, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia).[18] The average Atkinson index across the range of ε for the six regions ranges between 0.345 (North Eastern) and 0.388 (South Central).

[18] In her study of variations in inequality across U.S. metropolitan statistical areas, Madden (2000) also finds the greatest inequality in the South Central region.

Magnitude of the Policy Effects

So far, we have shown that the direction of policies' welfare effects are generally consistent across welfare measures. How do the magnitudes of these effects vary? There is no simple way to compare the magnitude of the effects using the traditional measures. However, the Atkinson measures have a dollar value interpretation, so comparisons across these measures is feasible.

According to our estimates, y_{EDE}, the equally distributed equivalent level of income, is 98, 88, 77, 52, or 38% of the average income when the Atkinson index parameter $\varepsilon = 0.1, 0.5, 1,$ 2, 2.5. In other words, if $\varepsilon = 1$, society could achieve the welfare associated with the actual income distribution with 23% less income if incomes were equally distributed across all adults.

A change in any of the government policies affects welfare. For example as Table 2 shows, a one dollar increase in the minimum wage raises the Atkinson index for $\varepsilon = 0.1$, 0.5, 1, 2, and 2.5 to 0.025, 0.123, 0.242, 0.503, and 0.646, which is 105%, 104%, 103%, 104%, and 105% respectively of the original level.

To illustrate the magnitude of the welfare effects of the minimum wage and other government policies, we use the change in the welfare loss, $L = \mu - y_{EDE}$ (Equation 2), which has the opposite sign of the change in y_{EDE}. In Table 3, we show the changes in dollar-denominated welfare loss that results from a 10% increase in the level of each policy variables (holding the other variables fixed).

The welfare effects of the minimum wage are larger in absolute value than those of the other policies. Historically, most minimum wage increases have been between 10 and 20%. All else the same, a 10% increase in the minimum wage in 1997 (roughly a half dollar) would have caused a statistically significant larger welfare loss (a fall in y_{EDE}) of \$11, \$44, \$76,

\$188, or \$269, respectively, for $\varepsilon = 0.1$, 0.5, 1, 2, or 2.5. Thus, the more weight we put on income transfers at the low end of the distribution, the greater the welfare harm of the minimum wage. If we multiply these average income effects by the U.S. adult population, then the "total loss of welfare" ranges from \$2 to \$54 billion. That is, we could achieve the same welfare level with between \$2 and \$54 billion less income by eliminating the 10% increase in the minimum wage.

Besides the minimum wage, the unemployment insurance, food stamp, and EITC programs are the only policies that reduce welfare, at least for some ranges of ε. The UI losses are substantial: The reductions in y_{EDE} are statistically significant for $\varepsilon \geq 1$ and are \$10, \$35, and \$55 for $\varepsilon = 1$, 2, and 2.5. Thus, the loss over the entire population ranges between \$2 and \$11 billion for $\varepsilon \geq 1$.

In contrast, AFDC/TANF, disability insurance, and EITC (for some values of ε) raise welfare (reduce the welfare loss from inequality). The statistically significant benefits from raising AFDC/TANF range from around \$3 to \$26 per adult, or \$600 million to \$5 billion for all adults. For disability insurance, the benefits range from \$3 to \$50 per adult and between \$600 million and \$10 billion for all adults. For $\varepsilon \geq 2$, an increase in the EITC causes welfare loss to statistically significantly decrease by \$114 to \$183, and \$23 or \$37 billion for all adults. An increase in the EITC phaseout variable raises welfare for the entire range of ε, with the per person welfare benefits ranging from \$21 to \$192, and total adult savings ranging from \$4 to \$38 billion.

Reliability of Results

To ensure that our results are reasonable, we first examine the effect of government policies on income distribution moments. Then we conduct a number of sensitivity analyses.

Effects of Government Policies on Income Distribution Moments

By regressing the first income distribution moment on government policies and other control variables, we can examine the effects of these policy on income levels. By examining how policies affect the first four moments, we gain a better understanding of how policies affect relative incomes and hence our welfare measures.

Before running our regressions, we rescaled the four moments so that they lie between zero and one on average: We divided the first moment by 10^4, the second moment by 10^9, the third moment by 10, and the fourth moment by 100. In contrast to the welfare measures that are scale free and only capture relative incomes, the first moment reflects the level of income. We regressed the first four moments of each state's income vector in each year on our basic set of policy, macroeconomic, and demographic variables as in Equation 4.

The average of the moments and the estimated coefficients on the policy variables are reported in Table 4. The minimum wage has a negative effect on the first moment: the average family income. A 10% increase in the minimum wage would cost the average adult approximately \$226 in annual income.[19] This finding is consistent with the results of Neumark et al. (2000). They observed that the increase from the minimum wage for low-wage workers is more than offset by a reduction in hours or loss in employment so that their incomes fall. Moreover, Lang and Kahn (1998) found that the minimum wage shifts employment from adults to teenagers and students (who are more likely than adults to be members of relatively wealthy families). Thus, in addition to having adverse relative income effects, the minimum wage lowers the average family income.

Table 4 also shows that the minimum wage coefficients are statistically significantly posi-

[19] During our period, the average real minimum wage is \$3.09, the hypothetical increase is 10%, the coefficient on the first moment is 0.0073, and first moment has been deflated by 10,000, so the average impact is \$226 = \$3.09 $\times$ 10% $\times$ 0.0073 $\times$ 10,000.

tive in the variance, skewness, and kurtosis regression. Thus, the minimum wage lowers the average income (first moment) and reshapes the income distribution so that there is more dispersion (second moment), a longer right tail (third moment), and thicker tails (fourth moment). All these changes to the income distribution contribute to making the income distribution more unequal according to any of the welfare measures.

The AFDC/TANF, EITC phaseout, and SSI have the opposite effect of the minimum wage. An increase in the AFDC/TANF and the EITC phaseout variable have the very desirable properties that they raise the first moment and lower the second, third, and fourth moments of the income distribution. That is, they raise the average level of income while making the income distribution more equal. The SSI has a similar effect (though the effects on the third and fourth moments are not statistically significantly different from zero).

An increase in EITC benefits raises the average level of income but increases the higher moments of the income distribution, making it less equal. An increase in food stamps lowers the average (reported) income. The national GDP coefficient in the first moment equation has an extremely large (approximate) t-statistic. It is, of course, a close proxy for average income within states.

Sensitivity of Results

To see how sensitive our results are to our assumptions, we conducted robustness experiments corresponding to each of our (apparently) critical 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.[20] The correlation coefficient between the

[20] 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.

weighted and the unweighted Atkinson indexes is 0.91 on average and the estimated coefficients from the weighted and unweighted version are identical up 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 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.[21]

Third, our regression specification includes the current minimum wage but not the lagged minimum wage. We did not include the lagged value because we were not convinced that it belongs in the equation, and it would create additional multicollinearity problems (the correlation between the minimum wage and its lag is 0.91).[22] However, because Neumark et al. (1997, 1998, 2000) and Baker et al. (1999) argued that the minimum wage may have important lagged effects, we experimented by including the previous year's minimum wage. For all the inequality indexes, both minimum wage coefficients were positive and jointly significant at the 5% level: the combined effect of the minimum wage and its lag is to increase inequality by more than in our original specification. Including the lag reduces the coefficient on the current minimum wage by between 24 and 91% but the sum of the coefficients on the current and lagged minimum wage ranges between 103% and 142% of the original coefficient.

[21] The t-statistics for the regression using the entire family income are larger than those we report.

[22] Including the lagged term requires an additional heroic assumption. The March CPS provides data pertaining to the survey year and the previous year. Hence in our regressions, we use the income and the minimum wage from the the previous year and the demographic characteristics and location of the current year. That is, we are assuming that the demographic characteristics were unchanged for one year. If we were to use the lagged minimum wage, we would have to assume that they were unchanged for two years.

Fourth, we controlled for many government policies, macroeconomic variables, and aggregate demographic variables, unlike most previous minimum wage studies. To examine how our results are affected by including these additional variables, we conducted four experiments. In the first experiment, we estimated the regression omitting the government policies other than the minimum wage. The estimated coefficients on the minimum wage and other control variables tended not to change qualitatively.[23] The minimum-wage coefficients are positive for the entire range of ε and statistically significantly different from zero at the 5% level for $\varepsilon \in (0, 1]$. The F-test on the hypothesis that all other government policy variables have zero coefficients is strongly rejected for the entire range of ε.

Our next experiment included all the policy variables and state dummies, but omitted the demographic and macro control variables. Except for the AFDC/TANF and disability insurance, the policy variables had statistically significant positive coefficients for the entire range of ε. We strongly reject the hypothesis that the control variables collectively have zero coefficients.

In our third experiment where we include only the minimum wage, state dummy variables, and year dummies (which cannot be included when we use either policy or macro control variables), we find that the minimum wage coefficients are positive for the entire range of ε and statistically different than zero at the 5% level for $\varepsilon \in [0.25, 2.25]$. Finally, we included only the minimum wage and the state dummies (we dropped the other government programs, the demographic, and macro variables). In this specification, an increase in the minimum wage statistically significantly reduces income inequality.

Taking all these experiments into account, we conclude that earlier studies that failed to control for macroeconomic and demographic factors may have drawn misleading conclusions

[23] Neumark et al. (1997), in their study of minimum wage's effects on poverty, reported that adding AFDC and welfare waiver control variables had little impact on their estimates of the effect of the minimum wage.

about the minimum wage's effects on the income distribution.

Within-Group and Between-Group Effects

Several recent studies of inequality (Karoly 1993, Murphy and Welch 1993, Burtless 1990, Levy and Murnane 1992) decomposed inequality by family or worker characteristics such as race, sex, education, or experience. These studies reported that the overall trend toward increasing inequality is the joint result of increasing within-group inequality and between-group inequality.

We divide the population into two groups: those families having at least one adult with at least a high school education (the high-education group) and others (the low-education group). The average (over the sample period) real family incomes of the high-education group is nearly double that of the low-education group: $18,575 versus $9,052.

We want to know how much of the welfare loss due to inequality, $L = \mu - y_{EDE}$ (Equation 2), is due to inequality within the high-education and low-education groups and how much is due to the differences in incomes between the groups? Blackorby et al. (1981) show that our overall Atkinson welfare loss can be decomposed into intra-group losses (weighted average of welfare loss within each subgroup) and inter-group (between group) losses.[24]

Blackorby et al. (1981) show that the intra-group (A) welfare loss is

$$L_A = \mu - \frac{1}{n} \sum_{k=1}^{K} n_k y_{EDE}^{k},$$

where y_{EDE}^{k} is the k^{th} group's equally distributed equivalent income, n_k is the k^{th} group's

[24] The Atkinson index has several desirable decomposability properties. Virtually the only other common inequality measures that have similar properties are the square of the coefficient of variation and the variance of logarithms (Foster and Shneyerov 1999).

population, and n is the total population. Similarly, the inter-group (R) or between group welfare loss is

$$L_R = \frac{1}{n} \sum_{k=1}^{K} n_k y_{EDE}^k - y_{EDE}.$$

Thus, the overall welfare loss from inequality is the sum of the intra-group and inter-group losses:

$$L = L_A + L_R \tag{5}$$

Consequently, a change in a government policy on overall welfare loss is the sum of its effects on intra-group and inter-group inequality.

To calculate L_A and L_R, we first determine y_{EDE}^k for the high-education and low-education groups. Next, we need to determine how intra-group and inter-group losses vary with government polices. To do so, we estimate equations analogous to Equation 4, where we regressed I on policy, macro, and demographic variables. Let I_A and I_R be the intra-group (A) and the inter-group (R) inequality measures that correspond to the overall inequality measure I:

$$I_A = 1 - \frac{\sum_{k=1}^{K} n_k y_{EDE}^k}{n\mu(y)},$$

and

$$I_R = 1 - \frac{n y_{EDE}}{\sum_{k=1}^{K} n_k y_{EDE}^k}.$$

All the estimated overall inequality indexes steadily increased inequality over our sample period, 1981-1997. For example, $I_2 = 0.44$ in 1981, 0.47 in 1990, and 0.53 in 1997. The percentage increase in Atkinson's from 1981 to 1997 were 45%, 36%, 28%, 21%, and 20% for $\varepsilon = 0.1$, 0.5, 1, 2, and 2.5. Nearly the entire increase in inequality was due to increases in the intra-group index. Indeed over this period, the percentage increases in I_A were 50%, 41%, 32%, 23%, and 21% for $\varepsilon = 0.1$, 0.5, 1, 2, and 2.5. In contrast, the corresponding percentage increases (or decreases) for I_R were 0%, -2%, -3%, 1%, and 4%. The ratio of the intra-group inequality to the overall inequality index is stable over our observation period, ranging from 92% to 95%, increasing slightly over time.

We regress I_A and I_R on the same right-hand-side variables as in Equation 4.[25] We use the results from the I, I_A, and I_R equations to determine how each policy affects L, L_A, and L_R. For example, using the I equation, we let Δx_i be the change in the relevant policy i, α_i be the estimated coefficient for that policy, then $\Delta I = \alpha_i \Delta x_i$, and $\Delta L = \mu \Delta I = \mu \alpha_i \Delta x_i$. The change in the intra-group welfare loss is $\Delta L_A = \mu \Delta I_A$. However, to calculate the change in the inter-group welfare loss, we replace μ with the weighted average of the equally-distributed-equivalent level of income of each subgroup: $\Delta L_R = \frac{1}{n} \sum_{k=1}^{K} n_k y_{EDE}^k \Delta I_R$.

Because we estimate the effects of changes in government policies using separate equations for L, L_A, and L_R, we are not guaranteed that the estimated effects of the policy change on the intra-group and inter-group welfare losses will sum to the overall loss. However, in most cases, the estimated change in the overall welfare loss is virtually identical to the sum of the changes. For each ε, the correlation between the change in the overall welfare loss and the change in the sum of the two submeasures as we individually increase each of the nine policies exceeds 0.99.

In Table 5, we show how a 10% change in each policy variable (holding the other policies

[25] We do not report the regression coefficients to save space. These coefficients are available from the authors.

fixed) affects the overall L, L_A, and L_R. An increase in the minimum wage raises inequality for the all ε (so y_{EDE} falls). Consider the social welfare function where $\varepsilon = 0.5$ (the third column of Table 5). The first row of the minimum wage section shows the effect of the change in the minimum wage for the entire population: A 10% increase in the minimum wage increases the welfare loss (lowers y_{EDE}) by \$44.39 per adult. [The bold text in the table indicates that the underlying coefficients for this effect is statistically significantly different from zero at the 0.05 level.] The two numbers below that one (second and third rows), show that the minimum wage change causes the intra-group welfare loss to rise by \$36.26 and the inter-group y_{EDE} to rise by \$8.08 (the two submeasures sum to \$44.34, which is close to the \$44.39 per capita loss for the entire population). Thus, 82% of the total fall in welfare from an increase in the minimum wage is due to intra-group changes and 18% is due to inter-group changes. For larger ε, virtually the entire change in welfare can be attributed to intra- rather than inter-group changes.

Similarly for the other policies, most of the change in overall welfare is due to intra-group rather than inter-group effects. The other policy variables besides the minimum wage that have large effects on equality are the EITC benefits and the EITC phaseout variables. The EITC benefits variable always has a statistically significant positive effect on the inter-group y_{EDE}. A 10% increase in the EITC benefits statistically significantly raises intra-group y_{EDE} for $\varepsilon \leq 1$, and lowers it for larger ε. Consequently, the overall effect on y_{EDE} is negative for small ε and positive for larger values.

Conclusions and Policy Implications

What can the government do to raise welfare by helping the poor? To answer this question, we examine the effects of seven 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 the minimum wage and the other 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 two 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. Second, the minimum wage, unemployment insurance, and food stamps – unlike other government programs – increase inequality according to all common welfare measures (though the unemployment insurance and food stamps results are not statistically significant for a few welfare measures). A 10% increase in the minimum wage (about 50¢) increases the welfare loss from inequality by between $2 and $54 billion depending on the welfare index used.

So how can the government most easily raise welfare? The greatest gains in welfare for most welfare measures could be accomplished by a 10% reduction in the minimum wage, followed by a 10% relaxation of the EITC phaseout restriction, a 10% increase in disability insurance, and a 10% rise in AFDC/TANF benefits.

By regressing the first four moments of the income distribution on our policy and other variables, we find that a 10% increase in the minimum wage would lower the average annual income per adult by $226 and would increase the variance, skewness, and kurtosis of the income distribution. These shifts in the distribution makes it less egalitarian by all our welfare measures. These results confirm that the minimum wage lowers average income and increases inequality according to all standard measures.

Most previous studies of the minimum wage have not controlled for other government programs, macroeconomic variables, and aggregate demographic variables. Our welfare results are not qualitatively sensitive to eliminating other programs but are reversed if the macroeconomic and demographic control variables are dropped. Thus, this difference in specification explains why our results vary from these earlier studies.

Finally, we decompose the effects of policies on Atkinson welfare loss into intra-group (within groups) and inter-group (between groups) effects. We examine this decomposition for families headed by people with a high school education or more and those headed by people with less education. We find that the minimum wage reduces equality for both low-education (less than high school diploma) and relatively high-education subpopulations and the between-group's income distribution. Virtually all of the increased welfare loss from an increase in the minimum wage is due to increases in intra-group inequality rather than between group inequality. The substantial rise in overall inequality from all factors over our sample period, 1981-1997, was due to increased intra-group inequality.

Appendix: Trimming

Before constructing our welfare measures, we must decide how to treat households that report negative, zero, or nearly zero incomes. For example in the 1981 California subsample, 118 families report no income and another 21 families report negative incomes out of 6,432 families. We drop families with nonpositive incomes because such incomes are implausible (one needs a certain minimal level of resources to survive) and because the Atkinson index and other welfare measures require the income vector be strictly positive.[26]

We found that including near zero, positive incomes hardly affects the Atkinson index if ε is less than one or greater than three. However, for the intermediate range, the index is very sensitive to the inclusion of a few observations near zero. Moreover, even if we allow the sample to grow extremely large, those few low value observations continue to dominate the index. We find all the regression analyses (OLS, GME, ridge) are highly sensitive to the inclusion of just a few of these low-value observations.

We want to remove these low observations because they are implausible and because they disproportionately affect the index. 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 (Cowell and Victoria-Feser 1996) to quantify the importance of an infinitesimal amount of contamination upon the value of statistic:

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

where y is the income vector with w being the weights, x is the data point of interest at the

[26] The CPS uses "top-coding," whereby it censors very high incomes. Fortunately, the Atkinson index and the other indexes that stress low incomes are not sensitive to such censoring.

lower end of the income distribution, and $\alpha = 1 - \varepsilon$. 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.

Table A 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 fewer than 4 families (average is 3.41 in "Mean" column), or around 0.31% of observations from each state-year subsample. The "Min." column shows that the fewest families we dropped was one, which we did for 283 individual state-year observations. The most we dropped ("Max." column) was 26 in California in 1985 (out of 5,440 families).

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Table 1: Summary Statistics, 1981-1997

Variables	Unit	Mean	Std. Var	Min	Max
Minimum Wage	dollar/hour	3.0870	0.2687	2.7016	4.2354
Unemployment Insurance	1000 dollar/week	0.1879	0.0791	0.0591	0.7176
SSI	1000 dollar/month	0.3233	0.0533	0.2618	0.6314
AFDC/TANF	1000 dollar/month	0.2934	0.1173	0.0748	0.6752
AFDC/TANF Need	1000 dollar	0.4253	0.1519	0.1734	1.2964
Disability Insurance	1000 dollar/year	0.3112	0.0393	0.2419	0.3826
Food Stamp	1000 dollar/month	0.1771	0.0299	0.0907	0.3002
EITC	1000 dollar/year	0.8426	0.3321	0.4812	1.3769
EITC Phaseout	1000 dollar	7.1924	0.9917	5.7748	8.4429
U.S. GDP	1,000 billion dollar	4.2799	0.5172	3.3774	5.1718
U.S. Unemployment Rate	percent	6.7294	1.3563	4.9000	9.7000
Education	percent	0.8691	0.0482	0.7027	0.9666
Female-Headed Family	percent	0.2397	0.0715	0.0859	0.4542
Age $<$ 18	percent	0.2799	0.0269	0.2137	0.3928
Age 18-29	percent	0.1786	0.0240	0.1115	0.2750
Age $>=$60	percent	0.1602	0.0265	0.0456	0.2322
Families with children under 6	percent	0.1628	0.0253	0.1072	0.2873
Family Size	number of person	2.4789	0.1483	2.1655	3.0476

Table 2: Welfare Index Regressions (approximate t-statistic below the coefficients)

	COV[a]	RMD[b]	GINI	SDL[c]	$I_{0.1}$	$I_{0.5}$	I_1	I_2	$I_{2.5}$
Minimum Wage[d]	**0.051**	**0.025**	**0.018**	**0.032**	**0.001**	**0.005**	**0.008**	**0.020**	**0.029**
	4.135	5.957	6.198	4.154	2.620	2.567	2.542	2.574	2.442
Unemployment Insurance	0.013	0.013	0.009	**0.039**	0.001	0.006	**0.013**	**0.049**	**0.077**
	0.418	1.695	1.585	2.562	1.142	1.551	2.106	3.099	3.128
SSI	-0.026	0.002	0.002	0.003	-0.001	-0.003	-0.003	-0.008	-0.016
	-1.773	0.341	0.432	0.236	-1.878	-1.268	-0.609	-0.583	-0.788
AFDC/TANF	**-0.089**	**-0.034**	**-0.021**	**-0.051**	**-0.004**	**-0.018**	**-0.031**	**-0.034**	-0.018
	-4.398	-5.068	-4.799	-3.696	-6.413	-6.411	-5.778	-2.711	-1.006
AFDC/TANF Need	0.009	-0.002	-0.002	-0.008	0.000	0.000	-0.002	-0.010	-0.019
	0.410	-0.281	-0.351	-0.635	0.002	-0.146	-0.353	-0.780	-0.991
TANF Reform	**0.059**	0.002	0.003	-0.004	0.002	**0.005**	**0.005**	-0.002	-0.005
	4.387	0.515	1.233	-0.745	3.923	3.201	2.032	-0.381	-0.647
Disability Insurance	**-0.101**	**-0.034**	**-0.027**	**-0.060**	**-0.003**	**-0.015**	**-0.025**	**-0.045**	**-0.052**
	-4.791	-4.442	-5.134	-3.661	-4.814	-4.688	-4.268	-2.648	-2.010
Food Stamp	-0.003	**0.019**	**0.011**	**0.040**	0.001	0.005	**0.013**	**0.030**	**0.031**
	-0.144	3.367	2.896	3.981	1.037	1.907	2.978	3.002	2.154
EITC	**0.057**	-0.007	-0.003	**-0.035**	**0.001**	0.003	-0.001	**-0.027**	**-0.043**
	3.047	-1.528	-0.967	-3.898	2.462	1.450	-0.261	-3.098	-3.450
EITC Phaseout	**-0.029**	**-0.007**	**-0.005**	**-0.010**	**-0.001**	**-0.004**	**-0.005**	**-0.008**	**-0.008**
	-9.962	-7.524	-8.366	-5.846	-9.836	-9.202	-8.088	-4.663	-3.074
U.S. GDP	**0.121**	**0.071**	**0.049**	**0.118**	**0.004**	**0.020**	**0.039**	**0.084**	**0.106**
	11.772	21.973	21.952	18.757	12.713	14.184	15.504	13.872	11.844
U.S. Unemployment Rate	-0.001	**0.005**	**0.003**	**0.012**	**0.000**	**0.01**	**0.003**	**0.009**	**0.011**
	-0.460	6.444	5.884	7.422	1.401	3.020	4.877	5.483	4.689
Education	**-0.075**	**-0.046**	**-0.025**	**-0.071**	**-0.006**	**-0.027**	**-0.047**	**-0.048**	-0.012
	-2.612	-5.949	-4.667	-5.092	-6.299	-7.307	-7.901	-3.512	-0.591
Female-headed Family	**0.221**	**0.072**	**0.049**	**0.110**	**0.009**	**0.038**	**0.061**	**0.075**	**0.059**
	6.728	7.345	7.187	6.022	8.026	8.146	7.825	4.163	2.208
Age $<$ 18	-0.005	0.005	0.003	0.022	0.000	0.002	0.006	0.016	0.021
	-0.287	1.039	0.881	2.437	0.449	0.918	1.584	1.803	1.517
Age 18-29	**0.067**	**0.019**	**0.016**	**0.034**	0.001	0.005	0.008	0.019	0.022
	3.054	2.862	3.473	2.359	1.752	1.634	1.541	1.306	1.007
Age $\geq$ 60	**0.063**	**0.033**	**0.024**	**0.035**	**0.002**	**0.007**	**0.012**	0.016	0.022
	2.954	5.568	5.898	3.118	2.720	2.844	2.649	1.410	1.319
Families with children under 6	0.002	**0.011**	0.005	**0.024**	0.001	0.005	**0.010**	0.024	0.031
	0.090	1.962	1.294	1.976	1.475	1.831	2.093	1.957	1.697
Family Size	**0.124**	**0.079**	**0.056**	**0.113**	**0.005**	**0.021**	**0.038**	**0.045**	**0.036**
	6.111	12.232	12.555	9.074	6.345	7.161	7.545	3.691	1.998
R^2	0.708	0.824	0.813	0.777	0.792	0.813	0.819	0.641	0.444
DW	1.854	1.785	1.774	1.815	1.776	1.771	1.768	1.771	1.866
ρ^e	0.080	0.303	0.274	0.256	0.169	0.221	0.268	0.140	0.062

[a]Coefficient of variation.
[b]Relative mean deviation.
[c]Standard deviation of logarithms.
[d]Coefficients statistically significantly different from zero at the 5% level are in bold face.
[e]First-order autocorrelation coefficient.

Table 3: Change in Welfare Loss (1997 dollars) from a 10% Increase in each Policy

ϵ	0.1	0.5	1	2	2.5
Minimum Wage[a]	**10.78**	**44.39**	**75.72**	**187.50**	**269.39**
Unemployment Insurance	0.80	4.33	**9.61**	**35.19**	**55.38**
SSI	-0.95	-2.92	-2.79	-7.36	-15.65
AFDC/TANF	**-3.12**	**-13.74**	**-23.38**	**-26.31**	-13.66
AFDC/TANF Need	0.00	-0.54	-2.24	-13.05	-25.61
Disability Insurance	**-3.26**	**-14.00**	**-24.11**	**-42.93**	**-50.09**
Food Stamp	0.42	3.04	**7.56**	**17.16**	**17.95**
EITC	**6.09**	14.366	-4.27	**-114.36**	**-183.09**
EITC Phaseout	**-20.54**	**-79.78**	**-123.12**	**-189.71**	**-191.90**

[a]Coefficients statistically significantly different from zero at the 5% level are in bold face.

Table 4: Income Moments Regressions (approximate t-statistic below the coefficients)

	Mean	Variance	Skewness	Kurtosis
Sample Average	$17,381	2.15e+08	2.8162	21.9519
Minimum Wage[a]	**-0.0073**	**0.0344**	**0.0039**	**0.0016**
	-3.9197	2.0254	2.7800	2.2294
Unemployment Insurance	0.0036	0.0377	-0.0012	-0.0000
	0.9524	0.8013	-0.4620	-0.0091
SSI	**0.0215**	**-0.0473**	-0.0015	-0.0003
	6.7040	-2.0777	-1.6827	-1.6126
AFDC/TANF	**0.0262**	**-0.0532**	**-0.0058**	**-0.0016**
	9.0485	-2.2739	-3.2506	-3.5813
AFDC/TANF Need	-0.0021	-0.0065	0.0022	0.0001
	-0.9080	-0.2550	0.9038	0.1088
TANF Reform	**0.0088**	**0.1295**	**0.0071**	**0.0050**
	5.8300	7.1018	3.9883	3.9249
Disability Insurance	0.0006	**-0.0392**	**-0.0035**	0.0001
	0.2105	-2.2871	-2.3296	0.6473
Food Stamp	**-0.0072**	-0.0401	-0.0008	**0.0003**
	-3.0810	-1.2329	-1.0303	3.3497
EITC	**0.0121**	**0.1777**	**0.0093**	**0.0059**
	5.5351	7.9373	4.3769	6.8078
EITC Phaseout	**0.0009**	**-0.0254**	**-0.0033**	**-0.0021**
	2.6492	-8.1184	-6.5643	-3.4339
U.S. GDP	**0.0419**	**0.0957**	**0.0073**	**0.0076**
	29.2273	7.6782	6.3392	10.6128
U.S. Unemployment Rate	-0.0002	**-0.0119**	**-0.0010**	**-0.0012**
	-0.4988	-5.5491	-2.9113	-3.9582
Education	**0.0219**	**-0.1229**	0.0003	0.0004
	6.8209	-3.4291	0.2184	1.4071
Female-headed Family	0.0074	**0.3114**	**0.0057**	**0.0013**
	1.7387	6.7421	3.0570	4.1963
Age $<$ 18	-0.0023	0.0298	-0.0004	0.0001
	-1.1410	1.3804	-0.5772	0.5539
Age 18-29	**-0.0068**	**-0.0810**	**0.0026**	0.0001
	-2.4330	-2.7103	2.6402	0.7432
Age $\geq$ 60	**-0.0101**	**-0.0657**	0.0013	0.0002
	-4.3546	-2.8493	1.1691	1.6653
Family with children under 6	0.0031	0.0391	-0.0013	-0.0001
	1.2268	1.7458	-1.4665	-1.6368
Family Size	**-0.0160**	-0.0451	0.0030	0.0006
	-6.0786	-1.6934	1.4986	0.9520
R^2	0.8625	0.8052	0.3967	0.2466
DW	2.0418	1.6280	1.9280	1.9429
ρ^b	0.7365	0.1862	0.0269	-0.0236

[a]Coefficients statistically significantly different from zero at the 5% level are in bold face.
[b]First-order autocorrelation coefficient.

Table 5: Decomposing the Effects of Policies[a] (1997 dollars)

ϵ	0.1	0.5	1	2	2.5
Average I_ϵ	0.0242	0.1184	0.2344	0.4838	0.6175
	0.0221	0.1083	0.2146	0.4511	0.5854
	0.0021	0.0114	0.0253	0.0601	0.0763
Average Welfare Loss	744	3642	7211	14883	18997
	680	3331	6602	13877	18009
	64	311	609	1006	988

Change in Welfare Loss from a 10% Increase in each Policy[b]					
Minimum Wage	**10.78**	**44.39**	**75.72**	**187.50**	**269.39**
	9.09	**36.26**	**60.41**	**167.69**	**251.15**
	5.28	**8.08**	12.53	10.69	7.61
Unemployment Insurance	0.80	4.33	**9.61**	**35.19**	**55.38**
	0.63	**3.82**	**9.41**	**35.21**	**53.52**
	0.05	0.51	0.60	2.15	3.37
SSI	-0.95	-2.92	-2.79	-7.36	-15.65
	-1.01	**-3.62**	**-5.09**	**-13.18**	-19.15
	0.22	0.34	1.30	3.41	0.69
AFDC/TANF	**-3.12**	**-13.74**	**-23.38**	**-26.31**	-13.66
	-2.54	**-11.19**	**-19.64**	**-26.76**	-12.56
	-0.34	**-2.91**	**-4.77**	-1.31	-0.34
AFDC/TANF Need	0.00	-0.54	-2.24	-13.05	-25.61
	0.13	-0.01	-1.01	-5.40	-11.32
	-0.30	-0.49	-0.64	-5.15	-8.24
Disability Insurance	**-3.26**	**-14.00**	**-24.11**	**-42.93**	**-50.09**
	-3.10	**-13.35**	**-23.29**	**-44.87**	**-57.00**
	-0.91	-0.63	-1.15	-1.55	0.16
Food Stamp	0.42	3.04	**7.56**	**17.16**	**17.95**
	0.22	2.01	5.51	12.98	12.47
	0.07	**0.95**	**2.20**	**4.77**	4.15
EITC	**6.09**	14.36	-4.27	**-114.36**	**-183.09**
	7.52	**22.45**	**14.24**	**-69.35**	**-120.82**
	-1.01	**-9.10**	**-19.68**	**-44.47**	**-40.29**
EITC Phaseout	**-20.54**	**-79.78**	**-123.12**	**-189.71**	**-191.90**
	-21.38	**-84.77**	**-132.98**	**-213.21**	**-218.35**
	-2.59	2.04	4.92	16.26	13.14

[a]For each category, the first line is for the entire population, the second line is for the intra-group inequality and the third line is for the between-group inequality. The average income is 30,764 for our sample period in 1997 dollars.

[b]Coefficients statistically significantly different from zero at the 5% level are in bold face.

Table A: Summary Statistics of Sensitivity Analysis

	Min.	1st Quan.	Median	Mean	3rd Quan.	Max.
Value of truncating point	100	100	180	213	280	1300
Number of families dropped	1	1	2	3.41	5	26
Percent of families dropped	0.04	0.15	0.24	0.31	0.40	1.38

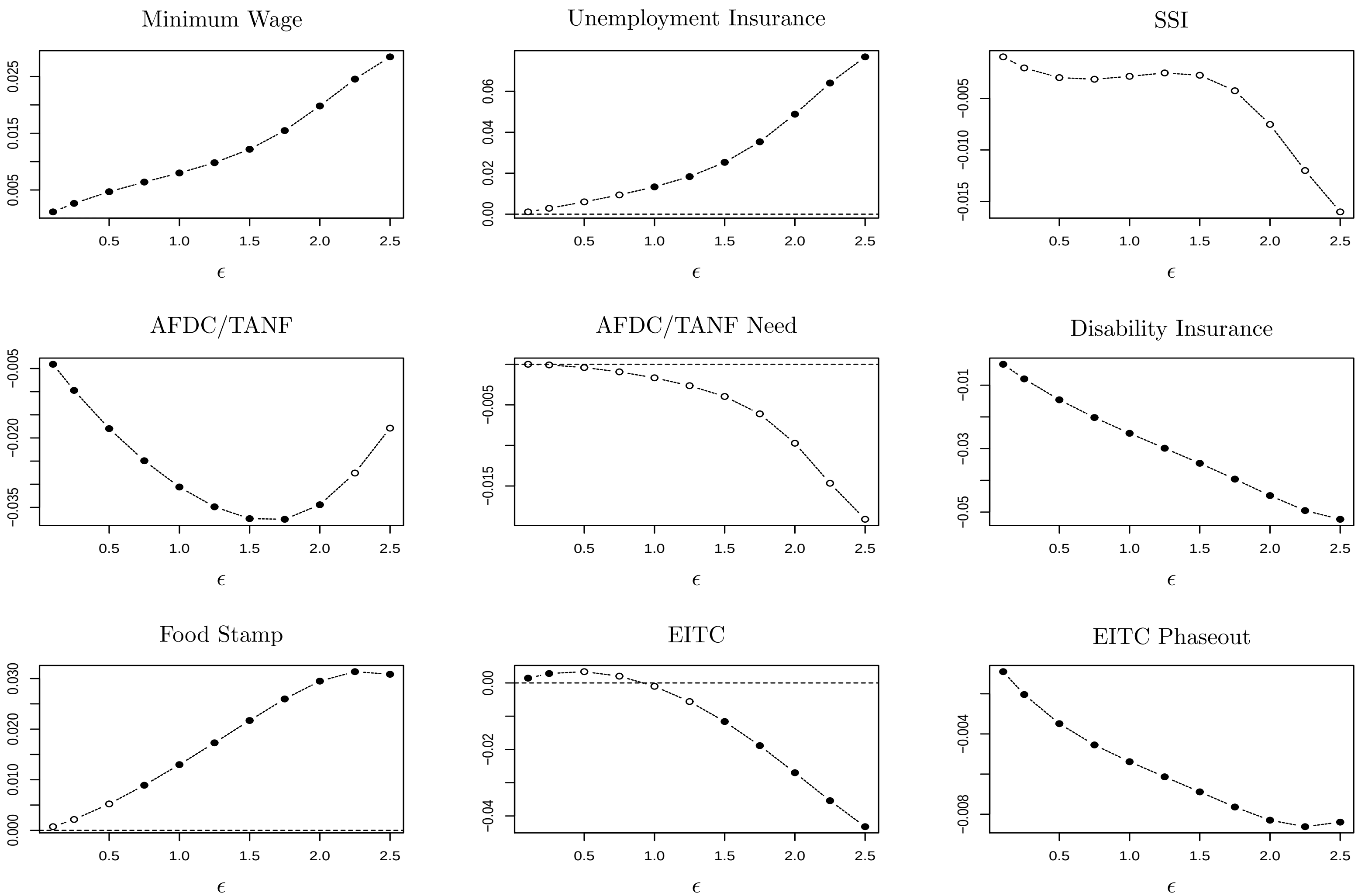

Figure 1: Coefficients of regression analysis with ϵ in [0, 2.5]. The coefficient is shown as a solid dot if it is statistically significantly different from zero at the 5% level; otherwise, it is represented as a hollow circle.