Online Appendix

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I Theory

I.1 The case without unemployment responses

In this Appendix, we consider the case where wages can freely adjust, but the conditional employment probability is exogenous at $p_i \in (0,1]$ (so $\frac{\mathbf{d}\mathscr{P}}{\mathbf{dT}} = \mathbf{0}$) and where the different types of labor are substitutable. More specifically, we assume that the different types of labor h_i and capital Z produce a numeraire good sold in a perfectly competitive product market under a constant returns to scale technology $F(h_1, ..., h_I, Z)$.[1] We furthermore assume the rate of return to capital, $r > 0$, is exogenous. The latter assumption can be viewed either by considering a small open economy and assuming perfect capital mobility, or by considering the steady state of a closed economy with infinite horizon savers. The assumptions of exogenous unemployment rates and constant returns to scale seem plausible in the long run, even though they ruled out job rationing considered by Landais et al. (2015) which are plausible in the short run. We then get that:

Proposition 1. *If the unemployment rates are exogenous, the production function exhibits constant returns to scale and* $\frac{\mathbf{d}\mathscr{C}}{\mathbf{dT}}$ *is invertible, the optimal tax schedule is given by:*

$$0 = (1 - g_j)h_j + \sum_{i=1}^{I} (T_i + b) \left. \frac{\partial \mathcal{H}_i}{\partial T_j} \right|^{Micro} \tag{1}$$

and depends only on microeconomic employment responses.

Proof: In the absence of unemployment responses to taxation $\frac{\partial \mathscr{P}_i}{\partial T_j} = 0$, the matrix $\mathcal{A}$ of corrective terms $\frac{\partial \mathscr{C}_i}{\partial T_j} + \frac{\partial \mathscr{P}_i}{\partial T_j} \frac{u(c_i) - d_i - u(b)}{p_i \, u'(c_i)}$ coincides with $\frac{\mathbf{d}\mathscr{C}}{\mathbf{dT}}$. We thus get: $\frac{\mathbf{d}\mathcal{K}}{\mathbf{dT}} = -\frac{\mathbf{d}\mathscr{C}}{\mathbf{dT}} \cdot \left.\frac{\mathbf{d}\mathcal{K}}{\mathbf{dT}}\right|^{\text{Micro}}$ and $\frac{\mathbf{d}\mathcal{H}}{\mathbf{dT}} = -\frac{\mathbf{d}\mathscr{C}}{\mathbf{dT}} \cdot \left.\frac{\mathbf{d}\mathcal{H}}{\mathbf{dT}}\right|^{\text{Micro}}$. Equation (14) then successively leads to:

$$\begin{aligned}
\mathbf{0} &= \mathbf{h} - \frac{\mathbf{d}\mathscr{C}}{\mathbf{dT}} \cdot \left.\frac{\mathbf{d}\mathcal{H}}{\mathbf{dT}}\right|^{\text{Micro}} \cdot (\mathbf{T} + \mathbf{b}) + \frac{\mathbf{d}\mathscr{C}}{\mathbf{dT}} \cdot \left.\frac{\mathbf{d}\mathcal{K}}{\mathbf{dT}}\right|^{\text{Micro}} \cdot \left(\left.\frac{\mathbf{d}\mathcal{K}}{\mathbf{dT}}\right|^{\text{Micro}} \right)^{\mathbf{-1}} \cdot (\mathbf{g}\,\mathbf{h}) \\
\mathbf{0} &= \mathbf{h} - \frac{\mathbf{d}\mathscr{C}}{\mathbf{dT}} \cdot \left.\frac{\mathbf{d}\mathcal{H}}{\mathbf{dT}}\right|^{\text{Micro}} \cdot (\mathbf{T} + \mathbf{b}) + \frac{\mathbf{d}\mathscr{C}}{\mathbf{dT}} \cdot (\mathbf{g}\,\mathbf{h}) \\
\mathbf{0} &= \left(\frac{\mathbf{d}\mathscr{C}}{\mathbf{dT}} \right)^{\mathbf{-1}} \cdot \mathbf{h} - \left.\frac{\mathbf{d}\mathcal{H}}{\mathbf{dT}}\right|^{\text{Micro}} \cdot (\mathbf{T} + \mathbf{b}) + \mathbf{g}\,\mathbf{h}
\end{aligned} \tag{2}$$

where the last equality requires the matrix $\frac{\mathbf{d}\mathscr{C}}{\mathbf{dT}}$ to be invertible.

Moreover, the firm's profit function verifies $\Pi(w_1, ..., w_I, r) \stackrel{\text{def}}{\equiv} \max_{h_1, ..., h_I, Z} \quad F(h_1, ..., h_I, Z) - \sum_{i=1}^{I} w_i \, h_i - r\, Z$. Applying the envelope theorem leads to $\frac{\partial \Pi}{\partial w_i} = -h_i$, thereby $d\Pi = -\sum_{i=1}^{I} h_i \, dw_i - Z\, dR$. Because of perfect competition and constant returns to scale, we get that $d\Pi = 0$, which together with

[1] We hence generalize Saez (2002) who considered perfect substitution across the difference types of labor through the production function:$F(h_1, ..., h_I) = \sum_{i=1}^{I} w_i \, h_i$, where w_i stands both for the productivity of labor in occupation i and for the wage in the corresponding labor market.

the assumption of an inelastic return of capital leads to $0 = \sum_{i=1}^{I} h_i \frac{\partial \mathscr{W}_i}{\partial T_j}$. In matrix notation, this implies that $\mathbf{h}$ is an eigenvector of Matrix $\frac{\mathbf{d}\mathscr{W}}{\mathbf{dT}}$ associated to eigenvalue 0. Hence, $\mathbf{h}$ is an eigenvector of Matrix $\frac{\mathbf{d}\mathscr{C}}{\mathbf{dT}}$ associated to eigenvalue -1, so $\frac{\mathbf{d}\mathscr{C}}{\mathbf{dT}} \cdot \mathbf{h} = -\mathbf{h}$ and eventually $\left(\frac{\mathbf{d}\mathscr{C}}{\mathbf{dT}}\right)^{\mathbf{-1}} \cdot \mathbf{h} = -\mathbf{h}$. Therefore Equation (2) simplifies to:

$$\mathbf{0} = \mathbf{1} - \mathbf{g}\,\mathbf{h} + \left.\frac{\mathbf{d}\mathcal{H}}{\mathbf{dT}}\right|^{\text{Micro}} \cdot (\mathbf{T} + \mathbf{b})$$

which corresponds to (1).

This result may look surprising and is also due to the specific representation of the labor supply responses along the intensive margin in the occupation model of Saez (2002). Stiglitz (1982), Naito (1999) propose alternatively a two-skills version of the Mirrlees model with intensive labor supply responses where low skilled and high skilled labor are imperfect substitutes. Stiglitz (1982) shows that the labor supply of the high skilled workers needs to be upward distorted (negative marginal tax rate for high skilled workers), unless the elasticity of substitution across the two types of labor is infinite. This result of Stiglitz (1982) looks at odds with the result above. Saez (2004) explains this discrepancy by the fact that in Stiglitz (1982) when a high skill worker earns the gross income intended to a low-skilled one, he does so keeping her high skill productivity. In other words, a worker's skill is portable across the different income levels in Stiglitz (1982) but not in Saez (2004). Therefore, a change in the low skilled gross wage affects the self-selection incentive constraint in Stiglitz (1982) and Naito (1999), as well as in the continuous income model of Rothschild and Scheuer (2013), while in the occupation model of Saez (2004) and Lee and Saez (2008), when an individual works in a low-skilled job, she has a low productivity. The occupation model captures not only extensive (participation) responses but also educational choice along the intensive margin in the long-run while the models of Stiglitz (1982) and Naito (1999) focus on the short-run hours of work and in-work effort responses along the intensive margin. □

II Simulations

We simulate the optimal tax schedule using a similar approach as Saez (2002). We denote the current tax system with the vector of occupation tax rates $\mathbf{t_0}$. The correpsonding density weights in the observed economy are given as $h_i^0 = \mathcal{H}_i(\mathbf{t_0})$.

II.1 System of Equations

The system of equations the determines the optimal tax schedule is given by the budget constraint:

$$b + E = \sum_{i=1}^{I} (T_i + b)\ \mathcal{H}_i(\mathbf{t}) \tag{3}$$

and the first order condition for each of the I income groups set to zero. Since we simulate the model in the no cross effects case we have that $\frac{\partial \mathcal{H}_j}{\partial T_i} = 0$ for $j \neq i$ and therefore:

$$(1-g_i)h_i + g_i h_i \frac{\left.\frac{\partial \mathcal{K}_k}{\partial T_i}\right|_{\mathbf{w},\mathbf{p}} - \frac{\partial \mathcal{K}_k}{\partial T_i}}{\left.\frac{\partial \mathcal{K}_k}{\partial T_i}\right|_{\mathbf{w},\mathbf{p}}} = -(T_i + b)\frac{\partial \mathcal{H}_i}{\partial T_i} \tag{4}$$

for $i = 1, ..., I$

Finally the first order condition for the optimal benefit level b (equation 10 in the main text) can be simplified under a no cross effects assumption for benefits (see below) to:

$$0 = -(1-g_0)h_0 + \sum_{j=1}^{I}(T_j + b)\frac{\partial \mathcal{H}_j}{\partial b} \tag{5}$$

In order to solve the system of equations we also have to parameterize $g_i(T_i)$ and $h_i(T_i)$. For the former we follow Saez (2002) and assume that $g_i = \frac{1}{\lambda c_i^{\nu}}$ with the curvature parameter $\nu = 0.5$ - the version in the paper - and $\nu = 1$ shown in the appendix. However, there is a complication, since $c_i = w_i(\mathbf{t}) - T_i$, but we do not have an estimate of how taxes affect pre-tax earnings. Therefore for the purpose of calculating the welfare weights, we will keep pre-tax earnings fixed at the observed levels and calculate c_i as $c_i = w_i(\mathbf{t_0}) - T_i$.

For h_i we use a first order Taylor approximation that is straightforward to implement given our estimates of the marginal taxes:

$$h_i = h_i^0 + \frac{\partial \mathcal{H}_i}{\partial T_i}\left(T_i - T_i^0\right) + \frac{\partial \mathcal{H}_i}{\partial b}\left(b_i - b_i^0\right) \tag{6}$$

Equations (1), (2) and (3) for $i = 1, ..., I$ thus constitute a system of I+2 equations and I+2 unknows: the marginal value of public fundsλ, the transfer for the unemployed b and the tax levels T_i for $i = 1, ..., I$.

II.2 First Order Condition for b

If we assume that benefits at zero do not affect pre-tax earnings or job finding probabilities for the working population, we get that:

$$\frac{\partial \mathscr{C}_j}{\partial b} = \frac{\partial \mathscr{W}_j}{\partial b} = \frac{\partial \mathscr{P}_j}{\partial b} = 0 \tag{7}$$

for $j \neq 0$. In this case, equation (10) simplifies to:

$$0 = -h_0 + \sum_{j=1}^{I}(T_j + b)\frac{\partial \mathcal{H}_j}{\partial b} + g_0 k_0 + \sum_{j=1}^{I} g_j h_j \left[\frac{1-p_j}{p_j}\frac{u'(b)}{u'(c_j)}\right] \tag{8}$$

The first term: $-h_0$ is the direct budget cost, the second term is the budget cost coming from employment responses. The third term represents the welfare effect of giving \$1 to the unemployed. The last term represents that an increase in b also benefits all individuals who participate in the labor market but fail to find a job. Note that they have a different welfare weight (which is because we defined social welfare as a function over expected utilities).

Suppose that the social welfare function is linear in individual expected utilities (benthamite). In that case: $\frac{u'(b)}{u'(c_j)} = \frac{g_0}{g_j}$. In that case equation (8) becomes:

$$
\begin{aligned}
0 &= -h_0 + \sum_{j=1}^{I} (T_j + b) \frac{\partial \mathcal{H}_j}{\partial b} + g_0 k_0 + \sum_{j=1}^{I} g_0 k_j \left[1 - p_j\right] \\
&= -(1 - g_0) h_0 + \sum_{j=1}^{I} (T_j + b) \frac{\partial \mathcal{H}_j}{\partial b}
\end{aligned}
\tag{9}
$$

III Description of Data Sources and Cleaning Steps

III.1 Data Sources

The empirical analysis combines information from several sources. This subsection describes each of the data sources used in this paper. In the subsections below, we describe how each of these are used to construct our final dataset.

1. Current Population Survey (CPS): The CPS is a monthly survey, sponsored by the U.S. Census Bureau and the U.S. Bureau of Labor Statistics (BLS), and is the main source of labor market statistics for the United States. The CPS sample is an overlapping panel of households that are randomly selected to participate in the survey. Information (including labor force status) is asked about each member of the household. For the first four months after their selection, households are surveyed monthly on the calendar week of the 19^{th} of each month about their labor market activities for the previous week. After their four months, households are not surveyed for eight consecutive months. Following the eight month of not being surveyed, households are surveyed again for four additional consecutive months. This is sometimes referred to as a $4-8-4$ sampling scheme. Households are asked about their regular weekly earnings and hours of work only in their fourth or eighth month of interviews. These households form the outgoing rotation group (ORG). Every March, the CPS supplements its standard questionnaire with additional questions on demographic characteristics and annual income, among others.[2] This supplement is referred to as the March annual data or the March Supplement. The March Supplement includes those scheduled to be interviewed in the March monthly CPS survey, as well as non-Hispanic White households with children 18 or younger and minority (Hispanic and non-Hispanic non-White) households drawn from CPS households that are in their eight month "off-period". We choose to supplement the ORG data with the March annual data because it increases our sample of households with children, especially lower income-households.

   Our individual (and aggregate) employment and labor force participation data comes from the monthly ORG and the March annual data of the CPS. In addition to the labor market variables, we extract demographic information on state of residence, education attainment, marital status and number of children for CPS respondents. The March annual data spans the time period 1984-2011, while the ORG data (from IPUMS) spans 1994-2010. Thus, each observation in the ORG and March annual data corresponds to a unique individual that is in a given month and year. Approximately 40 percent of our observations are interviewed

[2] While questions about labor force status (the *empstat* variable described in more detail below) are the same for the ORG and March supplement, some variables are not. For example, as we discuss below, annual earnings (the *incwage* CPS variable) are only available for those in the March Supplement. We use this information to impute earnings for all ORG and March Supplement households in year-by-education group cells.

in March, with the remaining observations (from the ORG) being equally distributed across the remaining months.[3]

2. Survey of Income and Program Participation (SIPP): We use information from the 1985 to 2008 SIPP panel's to construct AFDC/TANF and food stamp take-up rates for households with various numbers of children and income levels in each local labor market. We describe this procedure in detail in the following subsection.[4]

3. Federal Reserve Economic Data (FRED): We inflate all dollar amounts to 2010 levels using the national Consumer Price Index for All Urban Consumers (CPI) from the FRED. In some specifications, we also control for the seasonally-adjusted state unemployment rate. This information is also obtained from the FRED.

4. NBER TAXSIM software: Given the year, a household's state of residence, number of children and earnings, we calculate their net tax liability using the NBER TAXSIM software.[5]

5. Welfare Benefit Calculator: We use our own calculator constructed from the Welfare Rules Database. Given the year, a household's state of residence, number of children and earnings, we approximate welfare (AFDC and TANF) and food-stamps benefits.

III.2 Data Cleaning

III.2.a CPS Data

The CPS data cleaning process is divided into the following steps:

1. Correctly assign the number of children to the mother of a household

2. Keep only non-military single women

3. Drop observations with illogical responses

1. We first pool the ORG and March annual CPS cross-sections and merge this data to the FRED CPI and unemployment data. At this stage, we have 29,916,758 person-month-year observations spanning the 1984 to 2011 period. Each observation represents a unique individual. Next, we assign the number of children a mother is responsible for. This number is different for welfare benefit eligibility than for tax purposes. Specifically, welfare benefits vary with the number of children under the age of 18 in the household, whereas for tax purposes a child must be under the age of 19, or younger than 24 but in school. The key input in the raw CPS data for this calculation is the *momloc* variable. This variable indicates whether a respondent's mother is living in the household, as well as her "person number" if she is living in the household. For example, if there an individual's mother is not living in the household the value of the *momloc* variable would be equal to "00"; if the mother is the head of household, the value of the *momloc* variable would be "1".

To determine the number of children in the household for welfare benefit purposes, we sort the pooled CPS data by households and count the number of children under 18 living in the household. We assign this number to the head of household. Note that this number will include those

[3]From 1984 to 1993 we only have data from the March Supplement, so all observations for this period are for the month of March.

[4]We sometimes refer to the AFDC/TANF and food stamps programs as "welfare" programs.

[5]See Feenberg and Coutts (1993) for a detailed description of the TAXSIM software.

that are not biological children of the household head, consistent with the way welfare benefits are typically calculated. See Appendix B (below) for more details about welfare benefit calculations. For respondents between the ages of 16 and 24, the CPS variable *schlcoll* indicates whether the respondent was in high school or college during the previous week. The CPS variable *empstat* indicates the respondent's labor force status. We assign those that report not being in the labor force because they are in school ($empstat = 33$) or who report being in college or university full time ($schlcoll = 3$) and who are between the ages of 18 and 24 as children of the head of household. We add this count to the number of minors above in order to calculate the correct number of children for tax purposes.

2. After having assigned children to female household heads, we restrict the sample to non-military single women between the ages of 18 and 55 in the ORG and March annual supplement. Specifically, dependent children (7,449,217 observations), males (10,674,890), married women (7,093,086), those who report being less than 10 years older than their youngest child (1,977), those not in the ORG or March data (2,908,023), those under the age of 18 or over the age of 55 (600,843), those in the military (924) are dropped from the sample. At this state, we have 1,187,798 person-year observations spanning the 1984 to 2011 period.

3. We also drop observations where there is evidence that the data are contaminated. The CPS variable $wkswork1$ (available in the March Supplement only) indicates the number of weeks the respondent worked for pay in the previous year. The *incwage* (also available in the March Supplement only) variable captures the respondent's reported pre-tax earnings.[6] We drop women that claim positive earnings for the previous year (i.e. $incwage > 0$) yet report not working ($wkswork1 = 0$) (9,771 observations).

4. In the final data cleaning step we exclude those who report being full-time students (149,472 observations), those with more than seven children (215), those that report having negative non-employment (other) income (1,464), those that are the only person in their state-year-month education category (562). Dropping this final group is necessary for specifications where we estimate models with state-by-year-by-month fixed effects. Finally, we exclude those with a Bachelor's degree or higher, as they are unlikely to be affected by the tax-schedule at the bottom of the income distribution (234,343 observations).

The number of children assigned to a mother is an important input into eligibility for welfare benefits and for net tax liabilities. We assess how our measure of the number of children a mother is responsible for compares with the reported value in the CPS (the *nchild* variable in the CPS) in the cleaned sample. The following table reports the difference between our calculation and the reported number of children in the CPS. A value of 1 means that we calculate a female head of household to be responsible for one more child than she claims to be her own. For example, a respondent might fail to count any non-biological children she is responsible for. A value of 0 means that our measures are identical, while a value of-1 means the female head of household claims more of her own children in the CPS than we calculate. An example of this case could occur if a respondent counts a non-school age child living at home; our calculations would exclude this child for both welfare eligibility and tax purposes.In the overwhelmingly majority of case (90.23 percent), our calculated number matches the number reported in the CPS.

[6] In contrast to the labor force status questions that are asked each month for all CPS (ORG and March Supplement) respondents, the $wkswork1$ and *incwage* variables are only available for the March Supplement. This information is used below to estimate annual earnings for tax and welfare purposes.

$\Delta kids$	Count	Percent	Cumulative Percent
-7	4	0.00	0.00
-6	9	0.00	0.00
-5	46	0.00	0.01
-4	245	0.02	0.03
-3	1,969	0.20	0.23
-2	14,442	1.43	1.66
-1	70,288	6.97	8.63
0	909,305	90.23	98.86
1	8,028	0.80	99.66
2	2,253	0.22	99.88
3	803	0.08	99.96
4	256	0.03	99.99
5	83	0.01	100.00
6	24	0.00	100.00
7	5	0.00	100.00
Total	1,007,760	100.00	

III.2.b SIPP Data

We use information from the SIPP to calculate welfare (AFDC/TANF) and food stamp take up rates. The SIPP data cleaning process is divided into the following steps:

1. Extracting raw SIPP data
2. Ensure the data are comparable across SIPP panels
3. Calculate the number of children (under 18) in a family
4. Keep only single, non-military women age 18 to 55
5. Drop observations with illogical responses
6. Calculate welfare (AFDC/TANF/food stamps) take-up rates

1. We first pool cross sections from the 1985 to 2008 SIPP panels that span the years 1985 to 2012.[7] Respondents in each SIPP panel are interviewed every four months (a wave) for a two to four years.[8] Thus, each observation in our pooled cross-section is a person-month; the raw data include 24,401,516 such observations. We do not use the 1984 panel since it does not include individuals from Alaska, Montana, Nevada, New Hampshire, North Dakota, Utah and Vermont. Also, the 1984 panel does not differentiate between children's full time and part-time student status that is important for calculating welfare benefit eligibility.

2. Some variable names and response values differ across SIPP waves. For example, the variable indicating the age of the respondent is called *age* in the 1990 to 1993 SIPP panels, but is called *tage* beginning in the 1996 panel. Also, total family unemployment income is called $funemp$ in the

[7]At the time we extracted the raw data the most recent wave of the 2008 SIPP panel was wave 13 that covered the September 2012 to December 2012 period. As discussed below, we only use data up to 2011 to be consistent with the CPS data. At the time of writing, the most recent wave of the 2008 SIPP panel is wave 16, which covers the September 2013 to December 2013 perod.

[8]There are 14 SIPP panels; annual, overlapping panels from 1984 to 1993, 1996, 2001, 2004 and 2008.

1990 to 1993 SIPP panels; the variable name changes to $tfunemp$ beginning in 1996. Thus, the next step in the data cleaning process ensures that the data are comparable across SIPP panels. We use the code and crosswalk from the Centre for Economic Policy Research (CEPR) website that makes the 1990 to 2008 SIPP panels comparable.[9] We borrow from this code for earlier panels to ensure the comparability.

3. We calculate the number of children in a family as follows. We use information in the SIPP to designate women as family heads. Family heads can be living in the same household as their parents. In these cases, the woman would be designated as a sub-family head if she also has a dependent child. We classify all female family or sub-family heads as heads of household. Each person-month observation in the SIPP has common "family-level (or sub-family level)" variables, such as the number of children in the family/sub-family. We use this common family-level variable to calculate the number of children (that are under the age of 18, reside in the same household, and are related through birth or adoption) a female family or sub-family head is responsible for. [10]

4. Next, we restrict the sample to single non-military women between the ages of 18 and 55, as with the CPS data. First, we drop observations from the 2012 calendar year (116,624 observations). We drop males (11,640,919), those under 18 or over 55 (6,062,223), married women (3,959,793), those that are not heads of household (825,927), full-time students (120,822), those in the military (2,570), as well as a small number of those with more than seven children due to a lack of program data on these households (467).

5. As with the CPS data, we drop observations where there is evidence that the data are contaminated. We drop women who claim positive earnings for the previous year yet report not working. We also drop those that report working the previous year but have zero earnings (86,892 observations). The resulting sample size is 1,585,279.

6. We calculate AFDC/TANF and food stamps recipiency rates based on cells defined by an individual's year of observation, education group, and number of children. We calculate recipiency rates for each of these programs separately as follows. Using the cleaned SIPP data, we define our cells as follows. The four education groups are: less than a high school diploma (or equivalent), high school diploma, some college (or an associate's degree), and a college degree. The number of children groups are $\{0, 1, 2, 3+\}$. The year of observation groups are $\{1984-1988, 1989-1993, 1994-1998, 1999-2003, 2004-2008, 2009-2011\}$. The interaction of these groups leads to 96 cells. Thus, each observation in the SIPP will we an element of one of these cells. We calculate the fraction of individuals receiving AFDC/TANF and food stamps by calculating the fraction of women in each cell that report receiving benefit income.[11] Since women with no children are ineligible for AFDC/TANF benefits, the recipiency rate is zero in one quarter of the cells. In the empirical section we collapse the recipiency rates for the pre- and post-1996 years (after major welfare reform) for each education group. This leads to eight recipiency rates, one for each education group before 1996, and one for each education group after 1996.

III.3 Dependent Variables

Our dependent variables of interest are (a) the micro labor force participation rate; (b) the macro participation rate; and (c) the macro employment rate. We use information on the reported labor force and employment status from ORG and March CPS respondents to construct these three

[9] http://ceprdata.org/sipp-uniform-data-extracts/

[10] Since we only use the SIPP for welfare take-up rates we don't need to worry about children over 18 that are still dependents.

[11] The person-month probability weights in the SIPP are used to calculate these averages.

variables. The *empstat* variable (available for both the ORG and March Supplement) in the CPS indicates a respondent's employment status for the previous week.[12] The possible values for this variable are (i) "Not in labor force", (ii) "Unemployed", and (iii) "Employed".[13] For some years additional detail on a respondent's labor force status is available, but we do not use it in this paper. For example, information on whether those out of the labor force are unable to work is available for most years in the time period we study. In other years, reasons for being out of the labor force due to being in school full time is also available.

From the *empstat* variable we define an indicator variable equal to one if a CPS respondent is in the labor force and zero otherwise. Specifically, those that are coded as being "Unemployed" or "Employed" are in the labor force. Our macro measure of labor force participation aggregates this variable to the state, year and education group level (our definition of a local labor market). Similarly, we define an employment status indicator equal to one if a CPS respondent reports being "Employed" and zero otherwise; the employment/population rate. The macro employment status variable aggregates the employment status dummy variable to the state, year and education group level.

III.4 Tax and Benefit Variables

Our independent variables of interest are the net tax liability, after-tax income and welfare benefits of respondents. We assign each person in our CPS sample, the net tax liability and benefit amount corresponding to their state, year, education group, number of children and imputed earnings level. The first step is to impute earnings.

III.4.a Preliminaries: Imputed Earnings

We impute earnings as follows. Let w_i be the reported earnings by individuals in the March Supplement of the CPS, which indicates each respondent's pre-tax wage and salary income for the previous calendar year. For those with positive earnings, we take the natural logarithm of this variable $log(w_i)$. Next, for each year and education group (high school dropouts, high school graduates, and some college), we estimate the following model separately by education group e and year t:

$$log(w_i) = X_i\beta_{e,t} + \varepsilon_i,$$

where X_i are a set of demographic variables: a linear and quadratic term in age, dummies for race (hispanic and black) and urban/rural status and state fixed effects. The predicted values from these regressions (for each year and education group) are converted back into levels and assigned to all CPS respondents, regardless of their work status:

$$\hat{w}_i = exp(\widehat{log(w_i)}) = exp(X_i\hat{\beta}_{e,t})$$

This amount is inflated (or deflated) to 2010 dollars.

[12] The monthly CPS interviews (including those for the March Supplement) occur during the week of the 19th of the month. The baseline labor force status questions for each month (and therefore apply to the ORG and March samples) ask respondents about whether they were working, working but temporarily absent, searching for a job or not working and not searching for a job during the previous week, referred to as the "reference week" (i.e. the week of the 12th of the month).

[13] An individual is employed if he or she reports working or temporarily absent from a job during the CPS reference week. An individual is unemployed if they report not being employed but actively searching for a job during the reference week.

III.4.b Calculating Tax and Welfare Benefit Variables

Given imputed earnings, as well as a the TANF/AFDC and food stamps take-up rates, calculate the net tax liability and welfare benefits. We use the Urban Institute's Welfare Rules Database[14] and TRIM3[15] program rules to create an AFDC/TANF benefit calculator. For tax credits and liabilities we use the NBER's TAXSIM9 software[16].

Micro Tax and Benefit Variables: The micro tax and benefit variables are calculated as follows:

1. We group individual imputed earnings $\hat{w}_i$ into a grid with 200 dollar bins: {200, 400, 600,..., 120000}. We call this the binned imputed earnings: $\tilde{w}_i$. The reason for doing this is simply to ease the computational burden for calculating taxes and transfers.[17]

2. Let $G_\tau(w, s, t, n)$ be the tax policy function for tax/transfer program τ, for $\tau \in$ {federal taxes, state taxes, payroll taxes, AFDC, TANF, food stamps}, that maps earnings into tax liability depending on state, year and number of (dependent) children. We calculate G_τ separately for federal, state or payroll tax liabilities, as well as AFDC, TANF and food stamp benefit levels using our welfare calculator and TAXSIM9. Rather than using actual earnings we compute tax liability using the imputed binned earnings: $G_\tau(\tilde{w}_i, s_i, t_i, n_i)$

3. Let the take-up rate for tax/transfer τ be ρ_τ, which will be a function of education, number of children and period: $\rho_\tau(e, n, t)$

4. Let's define the Micro tax variable for individual i: $T_\tau^{micro}(i) = \rho_\tau(e_i, n_i, t_i) G_\tau(\tilde{w}_i, s_i, t_i, n_i)$, where $\rho_\tau = 0$ for $\tau \in$ {federal taxes, state taxes, payroll taxes}.

5. After-tax income conditional on working, c_i, for each individual in the CPS is calculated as follows:

$$
\begin{aligned}
c_i = \; & \tilde{w}_i \\
& - G_{Federal}(\tilde{w}_i, s_i, t_i, n_i) \\
& - G_{state}(\tilde{w}_i, s_i, t_i, n_i) \\
& - G_{Fica}(\tilde{w}_i, s_i, t_i, n_i) \\
& + \rho_{TANF/AFDC}(e, n, t) G_{TANF/AFDC}(\tilde{w}_i, s_i, t_i, n_i) \\
& + \rho_{FoodStamps}(e, n, t) G_{FoodStamps}(\tilde{w}_i, s_i, t_i, n_i)
\end{aligned}
$$

   where $G_{TANF/AFDC}(\tilde{w}, s, t, n)$ and $G_{FoodStamps}(\tilde{w}, s, t, n)$ are the annual levels of benefits for women with n children, binned predicted income $\tilde{w}$, living in state s, in year t, multiplied by the welfare take-up rate for groups defined by year, education and number of children. This accounts for the fact that the take up of these programs is less than 100 percent.

Macro Tax and Benefit Variables: The macro tax and benefit variables are calculated as follows.

1. First we collapse the individual tax variables $T_\tau^{micro}(i) = \rho_\tau(e_i, n_i, t_i) G_\tau(\tilde{w}_i, s_i, t_i, n_i)$ to the state X year X NumChildren X education level. Call this collapsed tax liability $T_\tau^{collapsed}(e, n, s, t)$.

[14] http://anfdata.urban.org/wrd/WRDWelcome.cfm
[15] http://trim3.urban.org/
[16] http://users.nber.org/ taxsim/taxsim9/
[17] Those with predicted earnings greater than $120,000 are topcoded at $120,000.

2. Let $N_{e,n}$ be the number of individuals with education e and n children, let N_e be the number of individuals with education e and define $\alpha_{e,n} = \frac{N_{e,n}}{N_e}$ to be the share of women with n children in education group e over the entire sample period and all states.

3. The Macro tax variable is constructed by integrating over the collapsed micro tax variables but using a constant distribution of children across all cells:

$$T_\tau^{macro}(e,s,t) = \sum_n \alpha_{e,n} T_\tau^{collapsed}(e,n,s,t)$$

III.4.c Instruments

Welfare benefits and tax liabilities, including tax credits such as the EITC, are endogenous to a taxpayer's earnings. We deal with this endogeneity using a simulated instrumental variables strategy. Our strategy exploits changes in tax and benefit rules across states over time between those with different numbers of children. Identification relies on holding fixed the distribution of income, which may be endogenous to tax policy. Our instruments are calculated as follows:

1. Calculate empirical CDF of real earnings w_i^r for each year and education group $F_{e,t}(\omega)$.

   We approximate the empirical CDF using centiles:

   First, we inflate the imputed income variable $w_{m,e,s,t,n}$ (see above) to 2010 dollars using the CPI. Using these imputed real incomes for all individuals from 1984 to 2011, we construct the percentiles of the empirical earnings distribution. We record the income cutoffs for the lower and upper bounds of each centile.

   To get the CDF by education and year, we compute the percentage of individuals in each centile. **taxes_simInst.ado** 78-127

   For each year we compute the mean nominal earnings in each centile, conditional on real earnings in that year being within the bounds of the centile from step 1. **taxes_simInst.ado** 144-166.

2. We then calculate the micro instruments by using our policy functions and the empirical CDF using the centiles:

$$T_\tau^{micro,Instrument}(t,s,e,n) = \int \rho_\tau(e_i,n_i,t_i) G_\tau(\tilde{\omega}_i,s_i,t_i,n_i) dF_{e,t}(\omega)$$

3. We then collapse the micro instrument: $T_\tau^{micro,Instrument}(t,s,e,n)$ to the state X year X NumChildren X education level. Call this: $T_\tau^{collapsed,Instrument}(e,n,s,t)$:

$$T_\tau^{collapsed,Instrument}(e,n,s,t)$$

4. The Macro Instrument is then calculated by aggregating across number of children, so that it only varies on the education X state X year level:

$$T_\tau^{macro}(e,s,t) = \sum_n \alpha_{e,n} T_\tau^{collapsed,Instrument}(e,n,s,t)$$

III.5 Variable List

For convenience, this subsection provides a list of all variables used in the empirical analysis. Since we use information from several sources, we record which dataset each variable originated from. Definitions for each variable are also included.

CPS Variables:

- *age*: age of CPS respondent
- *sex*: gender of CPS respondent (1 for males and 2 for females)
- *hisp*, *nonwhite*, *black*: race dummy variables from the CPS
- *marst*: marital status of CPS respondent (7 categories); singles are either divorced, widowed or never married
- *momloc*: indicates whether a CPS respondent's mother lives in the household. A value of 00 indicates that the mother is not in the household. Otherwise, the CPS person number of the respondent is coded. For example, if a CPS respondent's mother is the head of household, her person number would be 1.
- *statefip*: state of residence of CPS respondent
- *schlcoll*: Indicates whether CPS respondent's between the ages of 16 and 24 are in school. The acceptable responses are (CPS coded values in parenthesis): NIU (0), high school full time (1), high school part time (2), college or university full time (3), college or university part time (4), does not attend school, college or university (5)
- *educ*: a respondent's education attainment. The categories are (along with their coded values in the CPS in parenthesis):
  - NIU or no schooling: separate categories for no information available (001) or preschool/kindergarten (002), as well as a summary category (000)
  - Grades 1-4 inclusive: separate categories for each of grades 1 to 4 (011 to 014), along with a summary grades 1 to 4 category (010)
  - Grades 5 or 6: separate categories for grades 5 and 6 (021 to 022), along with a summary grades 5 to 6 category (020)
  - Grades 7 or 8: separate categories for grades 7 and 8 (031 to 032), along with a summary grades 7 to 8 category (030)
  - Grade 9: CPS respondent completed grade 9 (040)
  - Grades 10: CPS respondent completed grade 10 (050)
  - Grade 11: CPS respondent completed grade 11 (060)
  - Grade 12: separate categories for 12th grade completed with no diploma (071), 12th grade completed by diploma status unknown (072), 12th grade completed with a high school diploma or equivalent (073), as well as a summary variable for any one of these three categories (070)
  - 1 year of college: CPS respondent completed one year of college and did not earn a degree (080 to 081)

- 2 years of college: separate categories for Associate's degree, occupational or vocational program (091), Associate's degree, academic program (092), as well as a summary variable for each of these two categories (090)
- 3 years of college: CPS respondent completed three years of college (no bachelor degree) (100)
- 4 years of college: CPS respondent completed four years of college and earned a bachelor's degree (110 to 111)
- 5+ years of college: separate categories for 5 years of college (121), 6 years of college (122), completed a Master's degree (123), completed a professional school degree (124), completed a doctorate (125), as well as a summary variable for any one of these categories (120)

- $hsDrop$: dummy variable equal to 1 if a CPS respondent has less than a high school diploma (value of $educ < 72$); 0 otherwise (constructed variable)
- $hsGrad$: dummy variable equal to 1 if a CPS respondent has a high school diploma (value of $educ \geq 72$ and $educ \leq 73$); 0 otherwise (constructed variable)
- $college$: dummy variable equal to 1 if a CPS respondent has an associate's degree, vocational certificate or attended some college but did not complete a certificate or degree program (value of $educ > 73$ and $educ < 110$); 0 otherwise (constructed variable)
- $bachelor$: dummy variable equal to 1 if a CPS respondent has a bachelor's degree or higher (value of $educ \geq 110$); 0 otherwise (constructed variable)
- $wkswork1$: number of weeks a CPS respondent worked during the past calendar year
- $yearWork$: dummy variable equal to 1 if $wkswork1 > 0$; 0 otherwise (constructed variable)
- $incwage$: reported pre-tax wage and salary income
- $hrswork$: reported number of hours worked during the previous week
- $weekWork$: dummy variable equal to 1 if CPS respondent worked a positive number of hours during the previous week; 0 otherwise (constructed variable)
- $uhrswork$: number of hours a CPS respondent normally works during the week
- $hoursWork$: estimated number of hours worked last year; equal to $wkswork1 * uhrswork$ (constructed variable)
- $empstat$: a CPS respondent's employment status. The categories are (along with their coded values in the CPS in parenthesis):
  - NIU (00)
  - CPS respondent in the armed forces
  - CPS respondent's labor force status, conditional on being in the labor force: separate categories for employed at at work (10), employed but was temporarily not at work during the reference week (12), unemployed and an experienced worker (21), unemployed and a new worker (22) and a summary unemployed variable (20)

- CPS respondent's status (not in the labor force): separate categories for does housework (31), unable to work (32), in school full time (33), other (34), does unpaid work (35)

- lfp_ind: Labor force participation status dummy variable; equal to one if respondent is in the labor force ($empstat \geq 10$ and $empstat \leq 22$); zero otherwise (constructed variable)

- emp_ind: Employment status dummy variable; equal to one if respondent is employed ($empstat \geq 10$ and $empstat \leq 12$); zero otherwise (constructed variable)

IV Description of Welfare Program Rules and Calculation of Benefits

In this Appendix, we provide a brief description of the transfer programs that low-income families are eligible for. In particular, we summarize the following programs: Aid to Families with Dependent Children (TANF), Temporary Assistance to Needy Families (TANF), and the Supplemental Nutrition Assistance Program (SNAP). The SNAP program is often referred to as "food stamps". For simplicity, we refer to these programs collectively as "welfare". After describing these programs, we describe how we calculate individual welfare benefits using the rules published in the Welfare Rules Database[18] and TRIM3[19], managed by the Urban Institute.

IV.1 Description of Welfare Program Rules

IV.1.a Aid to Families with Dependent Children (AFDC)

The AFDC program was introduced in 1936 to provide financial assistance to children from low-income families. The program was replaced in 1997 by the TANF program following the passage of the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA), which we describe below. AFDC benefits were administered by the federal government, through the Department of Health and Human Services, although states shared in the program's costs and rule-making authority. In particular, states were able to determine individual eligibility and benefit levels, subject to federal guidelines and program requirements.

Families with children under the age of 18 that are residents of the state and whose children are living with them were eligible for AFDC benefits if they met the state's standard of need. A family was considered needy, if their monthly income was below a specified level; some types of income, such as child support payments, the EITC, and allowances for child care expenses, were disregarded for the purposes of determining eligibility.[20] As income increased above the disregard, a family's AFDC benefit was reduced until they were no longer eligible for benefits. Families that were eligible for the AFDC were automatically eligible for other entitlements, such as Medicaid and food stamps.

IV.1.b Temporary Assistance to Needy Families (TANF)

Two criticisms of the AFDC program was that the high claw-back rates on benefits and no duration limit on benefits provided a disincentive to work. These criticisms, among others, led to the replacement of the AFDC by the TANF program in 1997 as part of the PRWORA. In general, the primary difference between the AFDC and TANF programs is that the latter provides states

[18] http://anfdata.urban.org/wrd/WRDWelcome.CFM
[19] http://trim3.urban.org
[20] A household's eligibility also depended on meeting asset tests set by the federal and state governments.

with much more flexibility in choosing eligibility requirements, benefit levels, work requirements and phase-out rates. Under TANF, states are provided with block grants to finance their own programs, provided that they help achieve four goals set forth in the PRWORA.[21] The four goals are: (i) provide assistance to children from needy families, (ii) end the dependence of needy parents on government benefits by promoting job preparation, work and marriage, (iii) reduce out-of-marriage pregnancies, and (iv) encourage the formation and maintenance of two-parent families. States must ensure that TANF benefit recipients meet work requirements to remain eligible for benefits, with some exceptions.[22] The work requirements are that recipients: (a) must work as soon as they are job ready and no later than two years after initially receiving benefits and (b) work a minimum number of hours per week. Federal TANF rules also impose time limits on the receipt of (cash) benefits. Income (and asset) cutoffs for TANF eligibility varies significantly across states.

IV.1.c Supplemental Nutrition Assistance Program (SNAP or food stamps)

The Supplemental Nutrition Assistance Program (SNAP or food stamps) provides assistance to low- and moderate-income families to purchase food items. Rules for the food stamp program are determined by the federal government and is funded through United States Department of Agriculture. The program is administered by states that have some discretion in setting household income reporting requirements and choosing what the program is called in their state. SNAP benefits are delivered each month to households via a magnetically encoded payment card, known as an Electronic Benefits Transfer (EBT) card. After applying and getting approved for benefits, recipients receive their EBT card. States credit EBT cards for eligible households monthly. This card, similar to a debit card or a bank card, is accepted to purchase food items.

Eligibility for food stamps is primarily determined by a household's monthly income. The income test is increasing in family size. For households with one individual in 2015, the monthly income cutoff is \$1,265. The monthly income cutoff for households with two, three and four members is \$1,705, \$2,144 and \$2,584 respectively. A household's monthly allotment is calculated as $FS = (MaxBen - 0.3 * [(1 - EIDed) * EI + OtherInc - StDed - Shelt])$ where $MaxBen$ is the maximum allotment determined annually and dependant on the household size, $EIDed$ is the earned income deduction, $OtherInc$ is unearned income, which includes AFDC or TANF benefits, $StDed$ is a standard deduction and $Shelt$ is a shelter expense deduction[23].

IV.2 Calculating Individual Welfare Benefits

We calculate expected annual AFDC, TANF and SNAP benefits for each woman in our CPS sample using two databases of ruels. For every state and for each year from 1996 to 2013, the Welfare Rules Database contains detailed information on benefit levels (by household size), eligibility requirements, income disregards, work requirements and other details. For years prior to 1996 we use the AFDC rules from the Urban Institute's TRIM3 program structured similarly to the Welfare Rules Database. We assume that households have not exhausted their welfare eligibility throughout the analysis. We model the initial parameters of the welfare programs, some of the income

[21]The basic (nominal dollar) block grant for each state was set in 1996. States with faster population growth are eligible for larger block grants, and states can be eligible for more funding to deal with increased case loads during recessions.

[22]The activities that fulfill the work requirement varies by state.

[23]There is also an asset test of \$2,250 in financial resources. Recipients between the ages of 18 and 50 without dependent children also face work requirements. In particular, they are only eligible to receive SNAP benefits for three months in a 36 month period if they do not participate in a workfare or employment training program.

disregards expire or change after extended periods of sustained earnings. We use this information to construct separate welfare calculators for AFDC/TANF and food stamps. For each year and state, this calculator takes income, state, year and number of children and uses state disregards, claw-back rates and income tests to compute a household's monthly level of benefits. We multiply the level of monthly benefits by twelve as our measure of annual benefits for the OLS regressions.

Figure A-1 provides some example budget sets that our welfare / tax calculator generates. The figures show the different components that create the difference between pre- and post-tax income: food stamps, TANF/AFDC, state taxes and federal taxes. Both panels show the budget set of a single individual with 2 dependent children. As can be seen in the two examples (California and New York), food stamps have a structure like a negative income tax but with a cliff at the end, leading to a notch in the tax schedule. TANF pays a large amount at zero income and is then phased out though at different rates in different states (much slower in California for example). State taxes are essentially absent in California in the relevant range, but the federal EITC creates a sizeable bump in the 8 to 15 000 income range. In New York, state taxes create a small positive transfer at low incomes due to a state EITC, but have a negative effect above 30 000. The two figures highlight that there is substantial heterogeneity in these programs across states.

Figure A-2 shows the variation in the overall budget sets across number of children, time and states. Panels (a), (b) and (c) show how the budget sets by number of children have evolved in Ohio from 1984 to 2000, highlighting how the transfers have become more EITC-like with lower phase-out rates and somewhat smaller transfers at the bottom. Panels (c) to (f) show different states in the year 2000, revealing substantial heterogeneity in the shape and structure of these schedules. For example California's transfer schedule implies tax rate close to zero at low incomes up to around 10,000 but then the tax rate due to phase out of various programs is close to 100 percent between 10,000 and 30,00 for a single parent with two children. Compared to this Texas provides much higher work incentives (and much lower transfers at zero income). Overall these figures highlight the type of variation that identifies our micro responses (within labor market differential changes in taxes across children) and macro responses (across state and year changes on the labor market level).

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A Appendix Tables

Table A-1: Recipiency Rates of Transfer Programs

Period	(1) 1984-1996	(2) 1997-2011
Panel A: Food Stamps		
HS Dropout	0.414	0.406
HS Graduate	0.187	0.225
Some College	0.101	0.146
College Graduate	0.012	0.022
Panel B: AFDC/TANF		
HS Dropout	0.489	0.209
HS Graduate	0.230	0.100
Some College	0.170	0.062
College Graduate	0.030	0.011

Notes: Recipiency rates are calculated using the Survey of Income and Program Participation. These data reflect the recipiency rates of single women aged 18-55 who are not full time students or in the military, consistent with the data used for the empirical analysis from the CPS. An individual is counted as a recipient of either food stamps or AFDC/TANF if they received a transfer in any amount from the program. The recipiency rates for food stamps include single women without children. The recipiency rates for AFDC/TANF include only single mothers (single women without children are not eligible for the benefit).

Table A-2: OLS Regressions

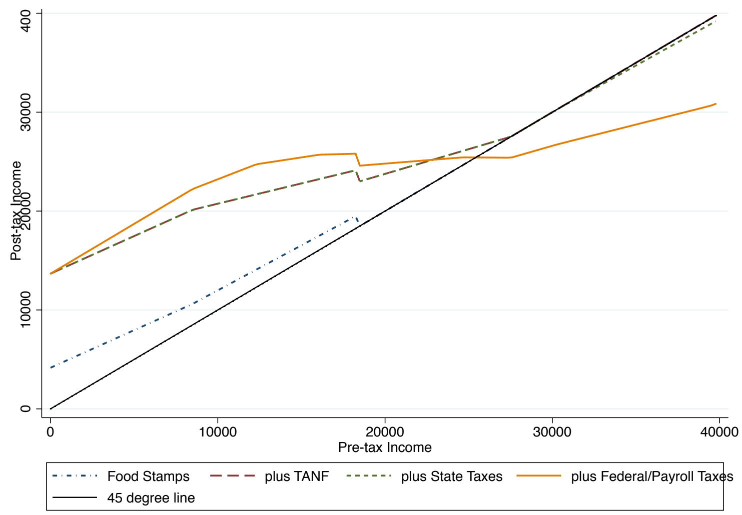
LHS Variable	(1) Participation	(2) Employment
Panel A: Micro Response	$\frac{\partial \hat{\mathcal{K}}_i}{\partial T_i}^{micro}$	$\frac{\partial \hat{\mathcal{H}}_i}{\partial T_i}^{micro}$
Taxes Plus Benefits $(T_i + b)$	-0.006 [0.001]***	-0.006 [0.001]***
Num. Obs	1816065	1816065
Panel B: Macro Response	$\frac{\partial \hat{\mathcal{K}}_i}{\partial T_i}$	$\frac{\partial \hat{\mathcal{H}}_i}{\partial T_i}$
Avg Taxes Plus Benefits within Labor Market	0.007 [0.001]***	0.009 [0.001]***
Num. Obs	8568	8568

Table A-3: Reduced Form Regressions

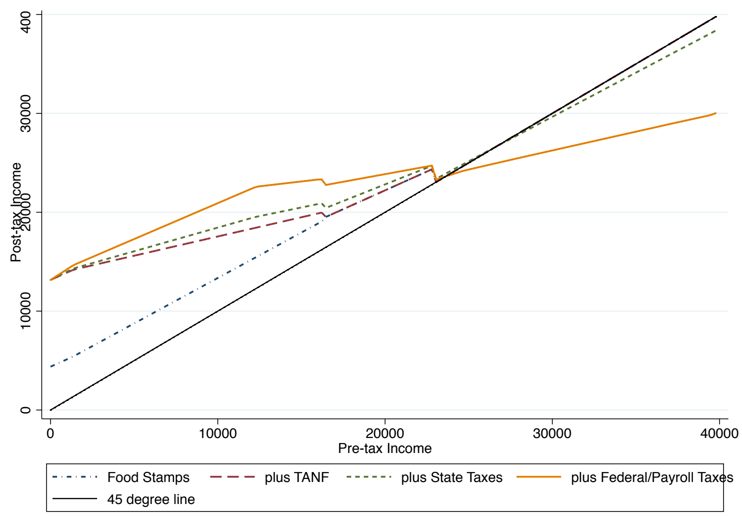
LHS Variable	(1) Participation	(2) Employment
Panel A: Micro Response	$\frac{\partial \hat{\mathcal{K}}_i}{\partial T_i}^{micro}$	$\frac{\partial \hat{\mathcal{H}}_i}{\partial T_i}^{micro}$
Taxes Plus Benefit with takeup: sim	-0.053 [0.003]***	-0.051 [0.003]***
Num. Obs	1816065	1816065
Panel B: Macro Response	$\frac{\partial \hat{\mathcal{K}}_i}{\partial T_i}$	$\frac{\partial \hat{\mathcal{H}}_i}{\partial T_i}$
Avg Taxes Plus Benefit with takeup: sim	-0.031 [0.015]*	-0.026 [0.016]
Num. Obs	8568	8568

B Appendix Figures

Figure A-1: Budget Set Components



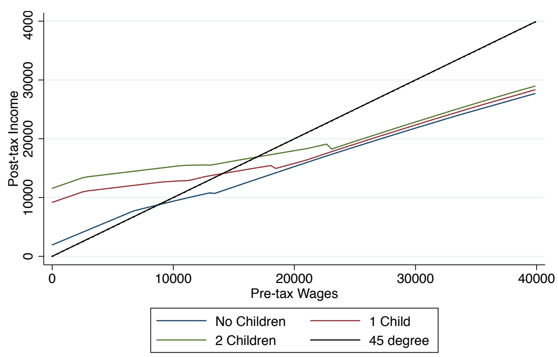
(a) California, Year 2000



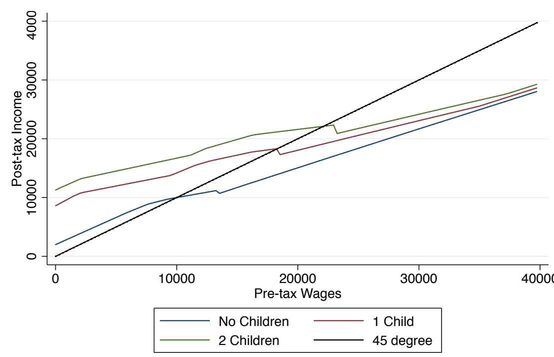
(b) New York, Year 2000

Notes: The figure shows the budget sets of a person with 2 children broken up by the individual components. The 45 degree line would be post-tax income in the absence of any taxes. The dashed blue line is pre-tax income plus foodstamps. The red line adds TANF, the green line adds state taxes and finally the yellow line adds federal taxes (including the EITC) and FICA taxes. Panel (a) shows the budget set for California in the year 2000. Panel (b) shows the budget for New York in the year 2000. The x-axis corresponds to pre-tax earnings, and the y-axis to post-tax and transfer income. Each line corresponds to the budget set of a single individual with either zero, one or two kids. The black line represents the 45 degree line.

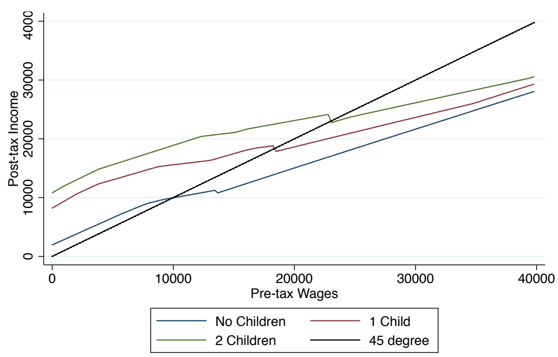
Figure A-2: Example Budget Sets for Selected States and Years



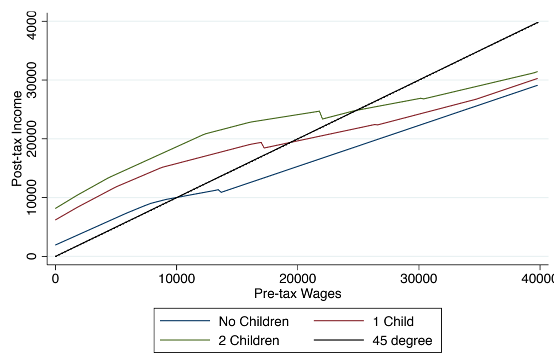
(a) Ohio, Year 1984



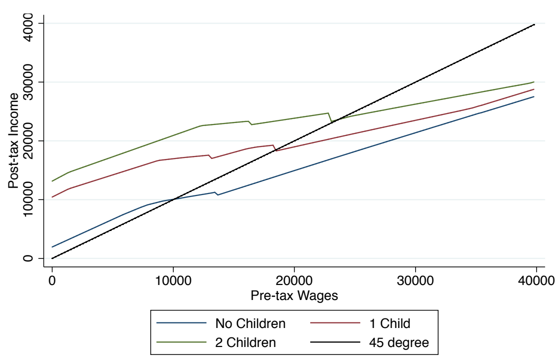
(b) Ohio, Year 1994



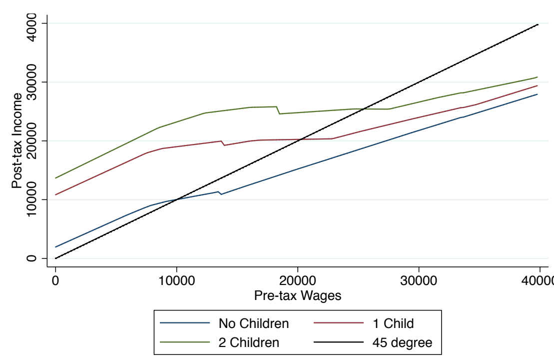
(c) Ohio, Year 2000



(d) Texas, Year 2000



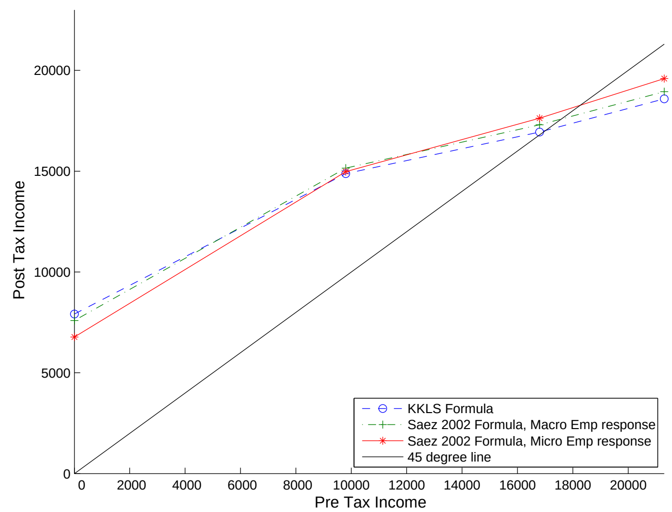
(e) New York, Year 2000



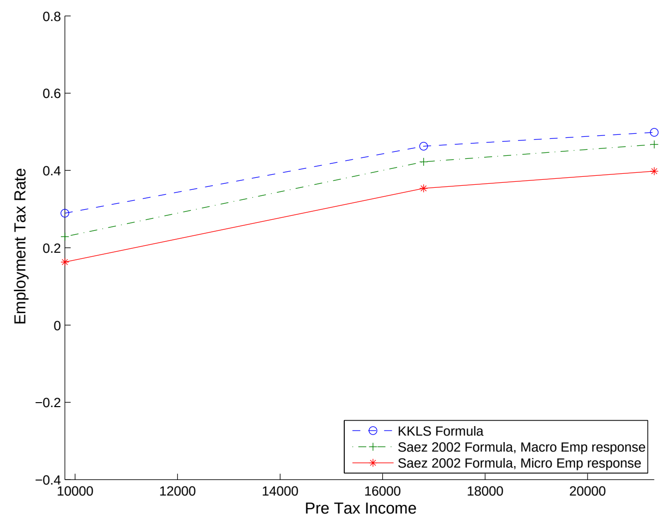
(f) California, Year 2000

Notes: The figure shows the budget sets of individuals in our sample by number of children for a selected sample of states and years. The x-axis corresponds to pre-tax earnings, and the y-axis to post-tax and transfer income. Each line corresponds to the budget set of a single individual with either zero, one or two kids. The black line represents the 45 degree line.

Figure A-3: Optimal Tax and Transfer Schedule Comparing KKLS Formula with Saez (2002) Formula, Redistribution parameter $\nu = 1$



(a) Comparing KKLS vs. Saez (2002) formula: Post vs. Pre-tax income

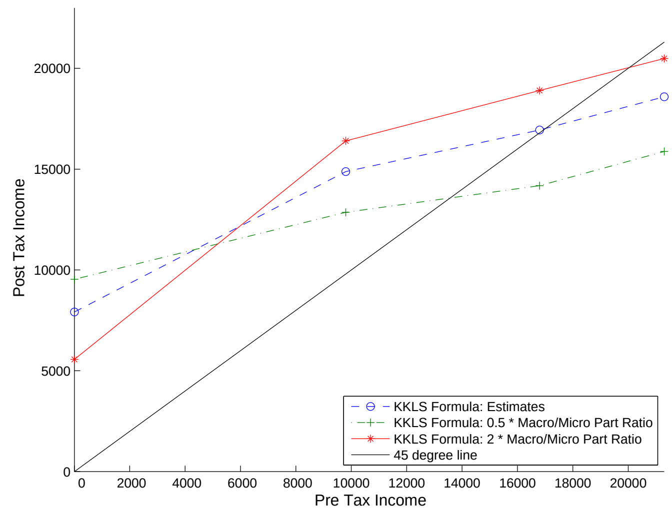


(b) Comparing KKLS vs. Saez (2002) formula: Employment tax rates

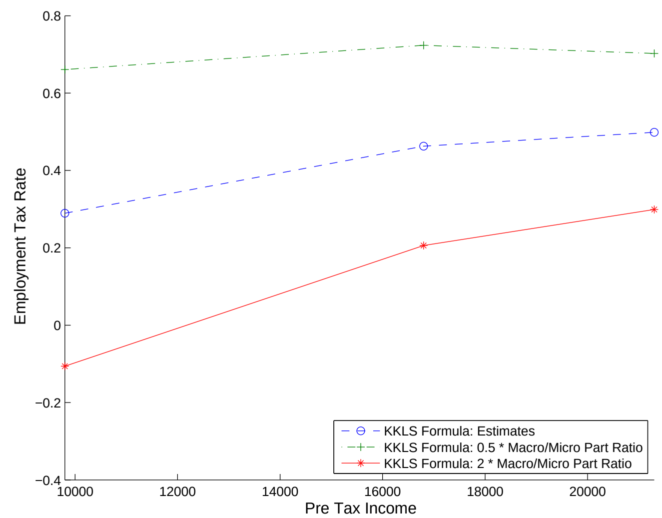
Notes: The figure corresponds to Figure 2 in the main paper, but with the parameter measuring preferences for redistribution ν set to equal 1 instead of 0.5.

Simulations of the optimal tax and transfer schedule under alternate assumptions on employment and participation responses. Distribution of the 4 income groups is calibrated using CPS data and corresponds to the 4 education groups in the empirical section. The figure uses the participation and employment responses estimated in the paper. The blue line uses the optimal welfare formula derived in this paper. The green line uses the Saez (2002) formula based on the estimated macro responses in this paper, while the red line uses the estimated micro employment responses in this paper.

Figure A-4: The Effect of Changing the Macro Participation Effect on the Optimal Tax and Transfer Schedule, Redistribution parameter $\nu = 1$



(a) KKLS formula with alternative macro vs micro participation rates: Post vs. Pre-tax income

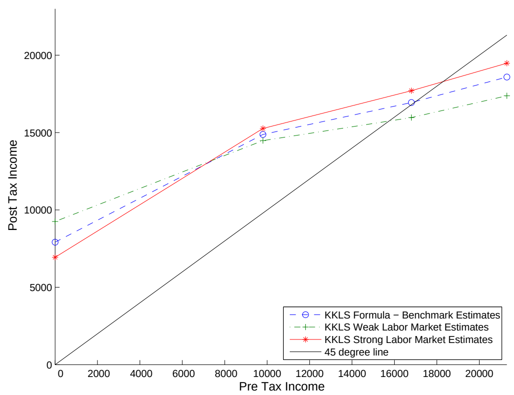


(b) KKLS formula with alternative macro vs micro participation rates: Employment tax rates

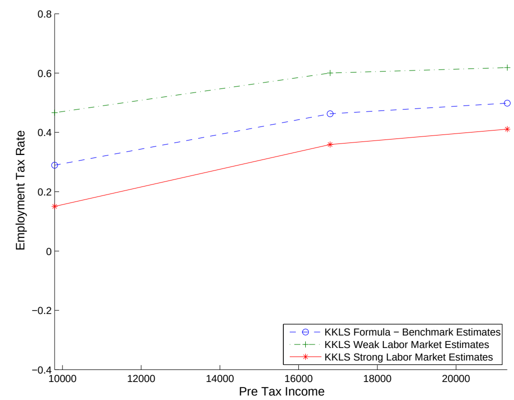
Notes: The figure corresponds to Figure 3 in the main paper, but with the parameter measuring preferences for redistribution ν set to equal 1 instead of 0.5.

Simulations of the optimal tax and transfer schedule under alternate assumptions on employment and participation responses. Distribution of the 4 income groups is calibrated using CPS data and corresponds to the 4 education groups in the empirical section. The top figure shows the post vs. pre-tax income relationship while the bottom figure shows the employment tax rates. The blue line shows the optimal tax schedule given the empirical estimates and the KKLS formula. The red line shows the optimal schedule if the macro responses are multiplied by 0.5 and the green line if they are multiplied by 2.

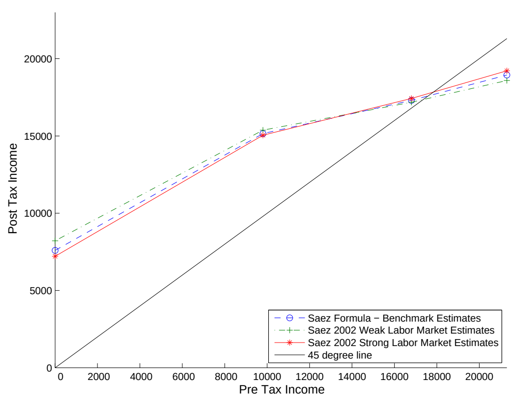
Figure A-5: Optimal Tax and Transfer Schedule in Weak vs. Strong Labor Markets, Redistribution parameter $\nu = 1$



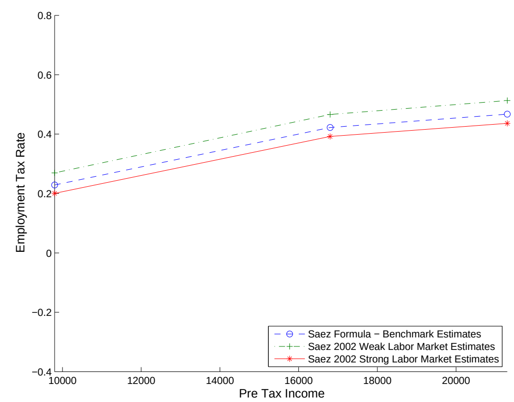
(a) KKLS formula: Post vs. Pre-tax income



(b) KKLS formula: Employment tax rates



(c) Saez (2002) formula: Post vs. Pre-tax income



(d) Saez (2002) formula: Employment tax rates

Notes: The figure corresponds to Figure 4 in the main paper, but with the parameter measuring preferences for redistribution ν set to equal 1 instead of 0.5.

Simulations of the optimal tax and transfer schedule under alternate macro participation responses. Distribution of the 4 income groups is calibrated using CPS data and corresponds to the 4 education groups in the empirical section. The top two figures use the KKLS optimal tax formula, the bottom two figures the Saez (2002) optimal tax formula using Macro employment effects. The blue line corresponds to the benchmark simulation using the estimated, participation and employment responses. The red line shows the tax schedule using the weak labor market estimates from Table 4 based on the 6 month change in the unemployment rate. The green line shows the tax schedule for the corresponding strong labor market estimates from Table 4.