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THREE ESSAYS ON EMPLOYMENT, INCOME AND TAXATION

by

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ABSTRACT

This thesis studies the implications of tax and transfer policy on income and employment, with emphasis on the low end of the income distribution. It also compares the labor market outcomes of recent veterans to those of veterans who served prior to 2001, when military utilization rates were much lower.

The first chapter observes that many overlapping income support programs exist in the United States, each with the goal of transferring resources to low income individuals with minimal employment disincentives. Each of the programs considered addresses this tension in a different way, potentially creating differences in the degree to which labor supply adjusts in response to program changes. I separately and simultaneously estimate labor supply elasticities associated with the income support programs in the context of a discrete choice model. The differences in elasticities I document across programs can inform both policy and optimal taxation theory.

In the second chapter I reassess whether the optimal income tax program has features akin to an Earned Income Tax Credit or a Negative Income Tax shape at the low end of the income distribution, in the presence of unemployment and wage responses to taxation. I derive a sufficient statistics optimal tax formula in a general model incorporating unemployment and endogenous wages. I then estimate the parameters using policy variation in tax liabilities stemming from the U.S. tax and transfer system. Using the empirical estimates, I implement the sufficient statistics formula and show that the optimal tax at the bottom has features that resemble those of a a Negative Income Tax relative to the case where unemployment
and wage responses are not taken into account.

In the third chapter, I compare labor market outcomes of veterans with post-2001 service time to those of similar veterans whose service did not extend past 2001. Veterans who served post-2001 are at a higher risk of long tours of duty, many of whom return with mental or physical disability. I find that veterans with post-2001 service are underemployed; conditional on employment however, veterans with post-2001 service earn at least as much, relative to veterans without post-2001 service.
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Do Workers Respond Differently Across Sources of Income: Evidence from Multiple Income Support Programs

1 Introduction

Most countries provide income support programs to transfer resources to low income individuals. Programs in the United States include the Earned Income Tax Credit (EITC), Temporary Assistance for Needy Families (TANF) which replaced Aid to Families with Dependent Children (AFDC) and the Supplemental Nutritional Assistance Program (SNAP, formerly Food Stamps). Each of these programs faces an important tension: provide resources to those who need them while minimizing erosion of work incentives. Providing income support to the non-employed may entice workers to leave the labor market and capture the transfer. On the other hand, transfers contingent on working create extra incentives to work, though work requirements might simply result in fewer resources to those who cannot work and are in most need of support.

Each of the programs listed above addresses this tension in different ways. For example, EITC provides benefits to low income wage earners, sidestepping the work disincentive altogether. However, EITC payments are disbursed through the tax code on an annual basis and there is some question regarding how well claimants understand incentives created by the tax credit. Survey evidence suggests that while most people are aware of the EITC, relatively few understand the nuances of the program, or how to maximize the credit (Romich and Weisner, 2000). However, peo-
ple’s earnings do bunch at the kink points created by the EITC (Saez, 2010), especially earnings of the self-employed who can more easily adjust their reported income, suggesting a sophisticated understanding of the rules. The degree of salience, even among taxes as prominent as sales tax, have real effects on behavioral responses (Chetty, Looney, and Kroft, 2009). AFDC did not have work requirements or time limits but relied on a caseworker determine eligibility. TANF introduced a stricter set of eligibility standards, time limits and work requirements when it replaced AFDC to disincentivize otherwise able bodied workers from reducing their labor supply. Given these differences, there is little reason to believe workers respond similarly to changes across programs.

In this paper, I test the hypothesis that labor supply elasticities across various income sources need not be equal. I focus attention on the labor supply response of low income single women. Focusing on single parent households simplifies the question; measuring the labor supply response of married couples requires modeling the joint work decision. The focus is on women since many of the transfer programs considered in this paper are a function of the number of children in the household, and there are far fewer single fathers than single mothers. I restrict attention to low income individuals due to their exposure to several different income transfer programs. Finally, I limit the labor supply decision to the extensive margin (to work or not to work) as a simplification; assuredly, this simplification is data driven. While high income individuals appear to respond significantly to changes in after tax wages along the intensive margin (Feldstein,

I begin by setting up a tractable framework to study the individual’s choice to work. The amount of income from each source or program the individual is eligible is a function of her the work decision. Each income source is represented flexibly to allow for the possibility that changes to income programs elicit differential labor supply effects. The individual maximizes utility over the choice to work or not. Since transfer programs target different sections of the income distribution, variations in labor supply responses could be due to income effects. I explore parameterizations of the model both with and without income effects.

From the model I derive labor supply functions that I estimate empirically. Using a welfare benefit calculator that I constructed from a database of program rules and a publicly available tax calculator, I exploit policy variation from several income sources over time and across states to estimate the effect that each policy has on the labor supply of low income single women. I find significant differences in the labor supply response across these transfer programs. Specifically, I estimate labor supply responses from programs associated with the tax code (e.g. EITC) to be larger than welfare type programs. I also estimate small but potentially important income effects.

Measuring and understanding the differences in the way workers respond to these programs is important for at least two reasons. First,

\footnote{See Chetty (2012) for a review of these papers.}
the labor supply responses determine how effective each program can be. Lower labor supply responses means smaller distortions. If workers do not adjust employment decisions to capture transfers to non-workers, a government can target transfers to different income groups with minimal distortions. Higher labor responses increase the ability of a government to attain an aggregate labor supply goal. Second, models of optimal taxation often rely on the magnitude of the labor supply elasticity of income (Mirrlees, 1971, Diamond, 1980, Saez, 2002). These models optimize the envelope of all tax and transfer programs. The optimal shape of the resulting budget set faced by workers depends on a labor supply elasticities that represent an average behavioral response to change in the of the underlying income sources. However, if the underlying programs elicit different elasticities, then two identical aggregate budget sets, with different compositions of income support programs, may deliver different welfare and labor supply outcomes.

The rest of the paper is structured as follows: Section 2 describes the income support programs I consider. Section 3 defines the simple discrete choice labor supply model I use to derive labor supply functions. Section 4 describes data that I use to estimate the parameters of the labor supply functions, and contains a discussion of the identifying variation each program provides. In Section 5.3 I estimate the parameters of the labor supply function, allowing for differences in responses across programs. In Section 6 I discuss some of the policy implications of the results. Section 7 concludes.
2 Income Support Programs

2.1 Federal Taxes

Federal tax liability for single women has evolved immensely since the 1980s. EITC expansions have been the major source of changes to federal tax liability. The EITC is a program that subsidizes the wage earnings of low income parents (and to a much lesser degree non-parents). Though EITC began small, following several expansions in 1986, the mid 1990s and again in the late 2000s, federal spending on EITC exceeded $65 billion for the 2013 tax year\(^2\). Obtaining EITC benefits, conditional on eligibility, is relatively simple and eligibility is straightforward. Benefits are disbursed along with taxes as a refundable credit; the claimant receives a refund for any benefit in excess of tax liability. To be eligible, the tax filer must have had positive earned income within the eligibility range, which depends on the number of children in the household, and investment income must be below the threshold ($3,350 in 2014). Claimants and their children must have a valid social security number and the claimant cannot be married filing separately.

The amount of the credit initially increases with income, and is phased out at higher earnings levels. In addition to earnings, the credit is determined by the number of dependent children in the tax filing household. Figure 1 displays the federal EITC schedule for various years, reflecting some of the expansions over the previous thirty years. Some of the EITC expansions created differential changes to the maximum benefit lev-

\(^2\)http://www.eitc.irs.gov/EITC-Central/eitcstats
els across the number of children in the household. Figure 2 displays the evolution of the maximum benefit by the number of children in the household. Notice that up until the early 1990s benefits were not dependent on the number of children (beyond one); by the mid 1990s households with two or more children were eligible for substantially higher credits than families with one child. In the late 2000s families with three or more children became eligible for higher benefits than families with two children.

Beyond the EITC, income taxes and child tax credits also determine federal tax liability. The child tax credit was created in the Taxpayer Relief Act (TRA) of 1997. Initially the credit was for $400 per qualifying child. The credit was increased in phases and as of 2015 the maximum credit is $1,000 per qualifying child. As income passes a threshold ($75,000 in 2015) the credit is phased out $50 for each additional $1,000 of income. Currently 15% of income over $3,000 is refundable. Individuals with income below $3,000 do not receive the child tax credit. The rules have changed since 1997, but the magnitude of these changes are much smaller than the EITC expansions. A third important piece of the federal tax code is the income tax. The bounds of the brackets are adjusted for inflation and marginal tax rates have changed very little for low income individuals over the past 30 years. Furthermore, while changes to EITC and child tax credits differentially affect mothers depending on the number of children she has, changes in income taxes do not differentially affect mothers across any observable (like number of children). The inclusion of year fixed effects in an empirical specification will absorb the time varying

\[ \text{See US code 24, accessible at https://www.law.cornell.edu/uscode/text/26/24} \]
aspect of income taxes. Changes to the EITC program represent the vast majority of the changes in tax liability, especially for low income single women.

2.2 State Taxes

State taxes vary both across state and within state, across time. State tax liability is primarily determined by income tax, EITC supplements and in a small number of states child tax credit supplements and rent or homeowners credits. The largest changes in state tax policy have been in the form of state EITC supplements. State EITC programs work much the same as federal EITC program; low income workers receive a supplement to their wages, on top of what the federal EITC program provides. Twenty-five states and the District of Columbia have implemented state EITC programs. Implementation dates range from 1986 (Rhode Island) to 2015 (California). Figure 3 is a chart of the state EITC implementation dates. Implementation across states has been steady since the mid-1980s. Most of the EITC supplemental programs are disbursed as a percentage of the federal EITC value and are typically refundable (as is the federal EITC). State income taxes are another source of cross-state variation in post-tax income. For single filers with $25,000 in taxable income in 2015 marginal tax rates range from zero in seven states to nearly 8% in Maine\textsuperscript{4}. As of 2015, only five states have child tax credit supplements paid as either a percent of the federal child tax credit or as a fixed amount.

\textsuperscript{4}http://taxfoundation.org/article/state-individual-income-tax-rates-and-brackets-2015
2.3 AFDC/TANF

Prior to 1996, Aid to Families with Dependent Children (AFDC) made up the bulk of what is often referred to as welfare in the United States. Created as a part of the Social Security Act of 1935, AFDC provided cash payments most often to low-income single mothers. Monthly benefits are maximum at zero income, and are phased out after an income disregard. The effective phase out rate depends on how low long an individual has had positive income. States are allowed to set maximum benefit levels but the income disregard and phase out rates were federally standardized. Figure 4 shows a typical AFDC schedule an individual would face when enrolling in AFDC.

By the mid-1990s, over 14 million individuals – or five percent of the population – depended on AFDC payments that totaled over $22 billion in nominal terms\( ^5 \). With phase out rates as high as 100%, critics of AFDC suggest that the program creates a strong disincentive for mothers to join the workforce. McKinnish, Sanders, and Smith (1999) estimate effective average tax rates of 35 to 40% for AFDC recipients over the years 1988-1991, exceeding marginal tax rates for the top income bracket (28-31 percent) over the same years \( ^6 \). Employment rates measured around 60 percent among single mothers between 1992 and 1995\( ^7 \).

Partially as a response to the low employment participation of AFDC eligible individuals and an increase in recipiency, many states applied for

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\(^6\) http://www.taxpolicycenter.org/taxfacts/displayafact.cfm?Docid=543

\(^7\) Tabulation from the Current Population Survey.
and were granted waivers to the federal program, increasing program flex-
ibility in an effort to encourage work and reduce caseload. The earliest
waivers were implemented in 1992 and by 1996 over half of the states
had implemented an approved program. In 1996 the US government
passed the Personal Responsibility and Work Opportunity Reconciliation
Act (PRWORA). PRWORA replaced AFDC with Temporary Assistance for
Needy Families (TANF), a program that created time limits and work re-
quirements for many single mothers seeking assistance. Stated goals of
the PRWORA include “end[ing] the dependence of needy parents on govern-
ment benefits by promoting job preparation, work, and marriage”. Like
many of the AFDC waivers that preceded, TANF afforded states much more
flexibility in of terms eligibility requirements, time limits and the benefit
calculation formula. Figure 5 shows a sample of four states that selected
very different benefit schedules by 1998. In general, states do not adjust
benefit levels for inflation annually, and though discrete increases in bene-
fits occur irregularly, the real value of TANF benefits has eroded over time.
In the five years following the passage of PRWORA, the number of families
receiving income assistance from TANF fell from 4.5 million to 2.2 million.
Welfare reform was largely perceived as a success as caseloads fell while
consumption levels remained constant or perhaps even increased through

8For details see http://aspe.hhs.gov/basic-report/state-implementation-major-

9Personal Responsibility and Work Opportunity Reconciliation Act of 1996. Accessible
2.4 Supplemental Nutrition Assistance Program

Supplemental Nutrition Assistance Program (SNAP), formerly known, and commonly referred to as Food Stamps, is a federal program providing additional resources to low income individuals with the requirement that the benefits be used to purchase food. Implementation of the food stamp program began state by state, beginning in the mid 1960s. By 1974 the program was operating nationwide. Originally, benefits were disbursed as physical coupons to the recipients. During the 1990s many states went to electronic benefit transfer (EBT) cards. As part of the PRWORA, states were required to use EBT for disbursement of SNAP benefits by October 1, 2002. The maximum benefit is allotted to families with no income. For families with income, benefits are reduced by 30 cents for each dollar of income after deductions. There is also an additional percentage disregard for earned income, as of 2015 workers could deduct 20 percent of earnings.

SNAP benefits are adjusted for inflation annually. Over time there have been a few incremental increases, beyond inflation adjustment, to the SNAP benefit levels. For the empirical Section of this paper I will not be able to identify a labor response from adjustments to SNAP due to lack of policy variation. However I do include SNAP benefits in the analysis due to important interactions with AFDC and TANF. Unlike EITC benefits, which do not interact with SNAP, AFDC and TANF benefits count as unearned income against SNAP benefits. Each additional dollar of AFDC or TANF an individual receives reduces their SNAP benefit by 30 cents. While this does create cross-state variation in effective SNAP benefits, the variation is collinear with state AFDC or TANF policy. AFDC/TANF and SNAP are
also linked in terms of receipt, many states have a common application and benefits are typically disbursed to the same EBT card. Users spend money from one program or another by entering a program specific PIN at the point of transaction. I discuss how I control for the direct interaction of SNAP and AFDC/TANF in Section 4.

3 Theoretical Framework

3.1 General Framework

In this section I develop a simple model of the labor supply decision for low income single women. This is a simple static model that only considers the extensive margin, the discrete choice whether or not to work. I make this simplifying assumption because the literature suggests that single women respond to work incentives more along the extensive margin than the intensive margin (Heckman, 1993, Meyer and Rosenbaum, 2001a, Eissa and Liebman, 1996). If the individual works, they will receive their potential earnings net of taxes, and transfers. If the individual does not work, earnings are zero but they receive income in the form of transfers. The individual does not choose the number of hours worked, or the levels of income conditional on work, they simply observe their potential income separately from all sources and choose their employment status. Individuals in the model also have an unobserved distaste for work. Utility
for individual $i$ is defined most generally in the following way:

$$U_i = \begin{cases} 
    u_{iw} = u(y_{i1w}, y_{i2w}, ..., y_{iPw}) - \chi_i & \text{if working (w)} \\
    u_{in} = u(y_{i1n}, y_{i2n}, ..., y_{iPn}) & \text{if not working (n)}
\end{cases}$$

where $l$ equals 1 if individual $i$ chooses to work and zero if not. $y_{pw}$ is income from source $p$ when the individual works (i.e. net federal tax liability) and $y_{pn}$ is the income from source $p$ when not working. $u(\cdot)$ is the utility the individual obtains from income sources. $\chi_i$ is the utility cost of working for individual $i$, unobserved by the researcher. However, I assume $\chi_i$ is a function of observable characteristics plus an unobserved idiosyncratic component:

$$\chi_i = f(X_i) + \epsilon_i$$

where $X_i$ is the vector of observables and $\epsilon_i$ is the idiosyncratic component. Given this framework, an individual will choose to work if their distaste for work is sufficiently small, specifically when:

$$\epsilon_i < u(y_{i1w}, y_{i2w}, ..., y_{iPw}) - u(y_{i1n}, y_{i2n}, ..., y_{iPn}) - f(X_i)$$

Changes to the income sources will induce individuals at the margin to enter or exit the workforce.

### 3.2 Heterogeneous Effects

I begin with the simplifying assumption that there are no income effects by assuming linear utility. When I actually estimate the labor supply
function I explore a parameterization that allows for income effects. The hypothesis I will test is whether workers react differently across forms of income. By introducing individual parameters for each income source, $\pi_p$, I allow that each can have differential effects on utility, and therefore behavior. Utility takes the form:

$$U_i = \begin{cases} \sum_{p=1}^{P} \pi_p y_{ipw} - \alpha \cdot X_i - \varepsilon_i & \text{if working (w)} \\ \sum_{p=1}^{P} \pi_p y_{ipn} & \text{if not working (n)} \end{cases}$$  \hfill (1)

where $\pi_p$ is the effect that income source $p$ has on utility. Now individuals choose work when:

$$\varepsilon_i < \sum_{p=1}^{P} \pi_p (y_{ipw} - y_{ipn}) - \alpha \cdot X_i$$  \hfill (2)

where $y_{ipw} - y_{ipn}$ is the change in income from source $p$ by moving from non-employment to employment. Again, the individual will choose to work only if their idiosyncratic realization of $\varepsilon_i$ is sufficiently small. Total labor supply will depend on where, in the distribution of $\varepsilon$, the value of the right hand side of equation (2) lies. The probability an individual works (and rate of employment) is:

$$\Phi \left( \sum_{p=1}^{P} \pi_p (y_{ipw} - y_{ipn}) - \alpha \cdot X_i \right)$$  \hfill (3)

where $\Phi$ is the CDF of the distribution from which $\varepsilon_i$ is drawn.
4 Data

The data I use for the estimation come from the Current Population Survey (CPS) via the Integrated Public Use Microdata Series\textsuperscript{10}. The CPS is the main source of labor market statistics in the United States and contains contemporaneous work status at the individual level as well as basic demographic information. Each household in the CPS is surveyed a total of eight times: two sets of four consecutive months separated by an eight month gap. Individuals being surveyed for the fourth consecutive month (surveys four and eight) comprise the outgoing rotation group (ORG). In March of every year, households are asked an additional set of questions. Importantly, the March supplement contains data on individual’s earnings from the previous calendar year. For the purposes of this exercise I focus on single women age 18 to 55 with less education than a bachelor’s degree, who are not in the military or enrolled full time in school. I focus on this subset of the population because they are most affected by income sources described in Section 2. The data I use for the estimation spans 1984-2011 (ORG data are limited to 1996-2010).

I created a benefit calculator to approximate the AFDC, TANF and SNAP benefits an individual is eligible for using rules provided by the Urban Institute. AFDC and SNAP rules come from the TRIM\textsuperscript{11} program rules database, and TANF rules are detailed in the Welfare Rules Database\textsuperscript{12}. AFDC and TANF rules are quite complicated and I have to make some simplifying assumptions. Some of the income disregards in the AFDC/TANF

\textsuperscript{10}Ruggles, Genadek, Goeken, Grover, and Sobek (2015)
\textsuperscript{11}http://trim3.urban.org/
\textsuperscript{12}http://anfddata.urban.org/wrd/WRDWelcome.cfm
benefit formula change over time; for calculation purposes I use the formula that is in effect as a person initially enters the program. I assume that single mothers are eligible for AFDC/TANF in terms of asset tests, have not reached their time limit and have no income other than wage earnings. To calculate federal and state tax liabilities I use the NBER’s TAXSIM9\textsuperscript{13} module for STATA. TAXSIM9 takes the tax year, household composition and income as inputs and calculates tax liabilities or credits separately by federal and state. I assume the woman files her taxes as head of the household, she claims her children as dependents and has no income other than wage earnings.

The framework laid out in Section 3 requires the researcher to observe disaggregated sources of income for each individual if they are working and if they are not working. Given wage earnings and demographics I can calculate the composite sources of income as stated above. To calculate income sources when an individual does not work I assume wage earnings (and total income) are zero. Calculating the income sources of those for whom I do not observe wage earnings is more difficult. I only observe wage earnings for the those that report positive annual earnings in the March CPS. I do not observe potential wage earnings for those that are not working or for any individuals in the ORG. To estimate potential earnings for individuals who report not working and for those not in the March CPS I impute wages based off of workers in the March CPS.

A second challenge is that I would like to identify work responses from policy changes alone. If the empirical wage distribution adjusts to policy

\textsuperscript{13}http://users.nber.org/˜taxsim/taxsim9/
then the income sources themselves are endogenous to the policy. As an example, suppose there were wage growth for a particular subset of the individuals relative to the rest, individuals in that subset might move into the labor force because the payoff from working has increased. The increase in wages will also lead to higher a EITC benefit (if the potential incomes lie in the phase-in range), using the OLS imputed wages would introduce positive correlation between effective EITC benefits and employment, but not due to a policy change. I want to identify labor supply responses from policy changes alone, holding wages constant. To do this I construct a simulated instrument, described later in Section 4.2.

4.1 Earnings Imputation

To impute earnings, I begin with the set of observations that contain annual earnings data (women in the March CPS who reported working in the previous year) and estimate the following equation, separately by educational attainment (high school dropout, high school graduate and some college, but less than a degree) and year cells:

$$\log(w_i) = \delta_s + \omega \cdot X_i + \varepsilon_i$$  

(4)

In addition to state fixed effects $\delta_s$, control variables within $X_i$ include a quadratic function of age, dummy variables for race and ethnicity, and a categorical variable describing the individual’s residence location (i.e. urban, suburban, rural). I use the coefficient estimates from the state fixed effects and the vector of demographics to predict log wages for all
individuals in the sample, whether I observe earnings or not, to keep the specification consistent across all individuals. EissaLiebman1996

Given an imputed income along with the state of residence, year and household size provided in the CPS, I am able to approximate net tax liability using TAXSIM and welfare benefits using the TANF/AFDC and SNAP calculator I created.

4.2 Simulated Instrument

I want to identify labor supply responses from policy changes alone, not from the evolution of the wage distribution. To do so, I construct a simulated instrument in the spirit of (Currie and Gruber, 1996). The idea is to fix the income distribution and calculate the evolution of income sources due to policy changes alone. The simulated instrument is constructed in several steps. First I aggregate all individuals in the CPS that report annual income (those who report working in the March CPS) and construct a distribution of real wages, adjusted for inflation using the Consumer Price Index for All Urban Consumers\textsuperscript{14}. Second I calculate the points in the distribution of real income that bound each centile. Third, separately by education group, I calculate the percentage of individuals in each centile. High school dropouts will have higher mass in the lower centiles relative to high school graduates and vice versa, but the sum of the percentages across centiles for each education group is one. These percentages will be used as weights later. Fourth, separately by year, I calculate a mean nominal income level conditional on being within each of the centile bounds of

\textsuperscript{14}From the Federal Reserve Economic Database, series CPIAUCSL
the aggregate real distribution from Step 2. Fifth, for the mean nominal income level associated with each centile I calculate taxes and transfers separately by state, year and number of children. Finally, for each education group, year, state, number of children I construct a weighted average for each income source using the weights in Step 3. I now have an average potential income associated with each source that is weighted by a static income distribution, specific to an education level for each state, year and number of children. I merge these income sources onto the CPS data and use them as instruments for the income sources generated from imputed income above.

Table 1 displays summary statistics for the simulated instrument. EITC credits are highest for those with the lowest income because more of them fall into the income eligibility range than those with a higher education whose earnings are more often in the EITC phase-out portion of the distribution or higher. State taxes are, on average, a liability for each education group but smaller for those with lower income. Benefits, in the form of AFDC/TANF and SNAP are highest for low education mothers. The last two rows combine all of the programs. Women with two children and a high school diploma or less education average net transfers, while childless mothers and college educated mothers of two average net tax liability when working. Figure 7 shows where the variation in each of the instruments comes from. Each variable is measured as a net increase in income due to employment, from indicated source. All of the graphs represent the simulated instrument for high school dropouts and are denominated in thousands of real dollars. A value of 1 means that becoming employed nets
the individual $1,000 from the income source. The left panel of each set
separates the variables by number of children. The right panel separates
variables across a selection of states, and displays values for a mother of
two children. Work incentives from all three programs have increased over
time. The change in incentives has been more extreme for mothers than
non-mothers, especially for federal and state taxes. The right panels show
that while there is no cross-state variation in federal taxes, there is con-
siderable cross-state and within-state cross-time variation in state taxes
and AFDC/TANF.

5 Estimation

5.1 Aggregating the Budget Set

Each of the income support programs considered in this paper affects
the budget set individuals face at the low end of the income distribution.
Figure (6) shows how all of the sources of income interact. This specific
collection of budget sets illustrate how I will test the main hypothesis.
All of these budget sets are for single mothers with two children in the
state of Ohio. The top graph is for 1992; the black line is the 45 degree
line. When there are no taxes or transfers pre-tax income equals post-
tax income and the budget set is the 45 degree line. The dot-dashed blue
line is the budget set when we include AFDC or TANF. Notice there is
a transfer of about $6,000 in AFDC or TANF for those with zero pre-tax
income. As income increases the AFDC/TANF line gets closer to the 45
degree line due to the phase out. The dashed red line traces out the budget
set if we consider both SNAP (conditional on AFDC/TANF income) and AFDC/TANF. Transfers at zero are even higher but the effective marginal tax rate is also very high. The green dashed line adds state taxes to AFDC and SNAP. Finally the solid orange line incorporates all adjustments to income including federal and payroll taxes. EITC and child tax credits push the budget set higher and reduce the marginal tax rate. This is the aggregate budget set.

The middle graph shows the budget set the same mother would face three years later, after an EITC expansion. The AFDC and SNAP lines are essentially unchanged, but the budget set pivots up due to the EITC. The third graph is two additional years later, in 1997. As Ohio transitioned from AFDC to TANF they changed the phase out rate, effectively pivoting the budget set up again. The change from the top to the middle graph increases gains from employment for low income single mothers through the EITC. The change from the middle to the bottom affects the aggregate budget set in the same way, but due to a change in AFDC/TANF. My hypothesis is that while these two changes may have had differential impacts on labor supply even though they had similar effects on the envelope of all income sources.

5.2 Estimating Equation

I begin with a linear approximation of the labor supply equation (3), later I will control for income effects. I collapse the data down to a cell defined by state, year, education group and number of children: the level of policy variation. The percent of sample women in a given cell that are
employed is:

\[ L_{s,y,e,k} = \sum_{p=1}^{P} \pi_p (y_{pw} - y_{pn})_{s,y,e,k} + \alpha X_{s,y,e,k} + \delta_s + \tau_y + \epsilon_i \]  

where \((y_{pw} - y_{pn})_{s,y,e,k}\) is the average change in income from source \(p\) when a single woman in state \(s\), and year \(y\), with education \(e\), and \(k\) number of children moves from not working to working. \(X_{s,y,e,k}\) is a vector of demographic and other controls including cell averages for age and age squared, controls for race ethnicity and state unemployment, fixed effects for number of children, educational attainment, year, month and CPS division\(^{15}\). The vector also includes the number of children that would not be eligible for medicaid if the mother earned her imputed wage\(^{16}\). It is difficult to place a monetary value on medicaid benefits so I do not interpret the coefficient in terms of an elasticity, but not including medicare eligibility changes could lead to omitted variable bias for the estimates of the other sources of income (if Medicare law changes are coincidental with state AFDC or TANF rules for instance).

For the estimation, I consider four sources of income (or liability): the federal tax code, the state tax code, AFDC or TANF benefits and SNAP. As discussed in Section 2, AFDC/TANF and SNAP interact in important

\(^{15}\)CPS divisions are geographic groups of three to eight states. There are nine divisions in total: New England, Mid Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific. Using CPS division fixed effects controls for common shocks that affect geographic regions of the United States, while exploiting some cross-state variation in policy. A concern when not explicitly controlling for state fixed effects is that state legislation could be a reaction to the economic conditions within the state. Controlling for state unemployment is an attempt to ameliorate this concern. I also include state fixed effects as a robustness check below.

\(^{16}\)These rules change by state and year, I thank Hilary Hoynes for sharing the eligibility parameters.
ways. While there is insufficient policy variation to identify labor supply responses, I account for SNAP in two ways. First, I simply control for changes in SNAP (mostly induced by state AFDC or TANF changes). Second, I combine of AFDC/TANF and Food Stamp benefits and estimate a single labor supply response from the two programs.

I use two stage least squares, using the simulated income change from each program calculated at the cell level, described in Section 4.2, as an instrument for the average change in income calculated using the imputed earnings.

5.3 Results

Table 2 displays the results from estimating Equation (5). Each variable listed is the income increase from a given source if an individual were to change from non-employment to employment. For instance an increase in the federal taxes variable could arise from an expansion of the EITC. In this case, federal tax credits for working individuals would increase while taxes at zero income remain unchanged. The expected sign on each of the coefficient estimates is positive. All else equal, increasing the income gain from working should increase labor supply.

Column 1 shows the estimate of the labor supply response to a change in aggregate income when moving from non-employment to employment. This is a common method to generate the labor supply elasticity used to calibrate an optimal taxation model. For the first column I calculate the implied elasticity as:
\[ \eta = \frac{\partial L_{s,y,e,k}}{\partial(Y_w - Y_n)_{s,y,e,k}} \cdot \frac{Y_w - Y_n}{\bar{L}} \]

where \((Y_w - Y_n)_{s,y,e,k}\) is the total change in income from employment for a given cell. \((Y_w - Y_n)\) is the average total income change across cells, \(L_{s,y,e,k}\) is the employment ratio at the cell level and \(\bar{L}\) is the average employment ratio across cells. The implied elasticity for total income, shown in the bottom panel, is 0.33 which is in line with much of the existing literature (see Chetty (2012)). Column 2 displays the results when I allow for heterogeneous effects across income sources. The implied elasticities for columns 2-4 are calculated as:

\[ \eta_p = \frac{\partial L_{s,y,e,k}}{\partial(y_{pw} - y_{pn})_{s,y,e,k}} \cdot \frac{Y_w - Y_n}{\bar{L}} \]

where \((y_{pw} - y_{pn})_{s,y,e,k}\) is the income change from source \(p\) for a given cell. The interpretation is a one percent change in total income due to a change in source \(p\) induces an \(\eta_p\) percent change in the employment ratio. The results in Column 2 suggest labor responses from changes in the federal tax code, and across states, within a division, appear greater than the responses associated with changes to income from AFDC or TANF. In the bottom panel, the \(\chi^2\) and p-value listed are associated with a test that the three coefficients are equal. The hypothesis can be rejected, suggesting the responses are indeed different across programs. The differences between Columns 1 and 2 are also important for optimal tax theory, using only the labor supply elasticity of total income to calibrate a model could be misleading.
In Column 2, I estimate a labor supply response for AFDC or TANF and control for SNAP separately. In Column 3, I combine the two programs and measure net effects of changes to AFDC or TANF and Food Stamps. I do this because of the interactions of the programs described in Section 2. Combining the programs does not meaningfully change the results. The implied elasticities from changes to AFDC or TANF and SNAP remain much smaller than elasticities coming from the tax code.

Finally, in Column 4, I introduce an indicator variable that equals one for each year after TANF replaced AFDC (beginning in 1997). I interact the dummy with the “AFDC/TANF and SNAP” variable to allow for a differential effect across AFDC and TANF. In this column, the estimate labeled “AFDC/TANF and SNAP” is the estimate for only the AFDC regime. The estimate labeled TANF and SNAP is the interaction with the time dummy. The sum of the last two estimates is the estimated elasticity for the TANF regime. There are many reasons to believe labor supply responses may be different across these two welfare regimes. States adjusted eligibility rules, work requirements, time limits and other parameters. Empirically, however, the labor supply response across the two programs are indistinguishable; the interaction term is essentially zero.

That the labor responses to federal taxes and state taxes are quite similar across specifications is an interesting result. The source of variation from federal taxes is largely due to EITC expansions, a program that even claimants do not usually display an understanding of the details (Romich and Weisner, 2000). While much of the variation at the state level is due

\[17\] I have also used an indicator variable equal to one for an AFDC waiver and TANF, the results are unaffected.
to cross-state income tax variation.

Table 3 displays a set of robustness checks using different geographic fixed effects. Column 1 in Table 3 is the same as Column 4 in Table 2 and is provided for comparison. Table 3 Column 2 replaces division fixed effects with state fixed effects. Column 3 replaces division fixed effects with region fixed effects, a coarser geographic grouping of states. Columns 4 - 6 interact geographic fixed effects with the year fixed effects. Estimates for federal taxes and AFDC/TANF and SNAP are robust to the choice of geographic fixed effects. However controlling for state fixed effects absorbs the identifying variation; estimates on state taxes are essentially zero. This suggests that most of the labor supply response from the state tax code comes from cross-state level differences in income taxes as opposed to within-state changes to EITC supplemental programs.

One may be concerned that if federal and state taxes tend to affect different portions of the income distribution than AFDC/TANF and Food Stamps, differences in estimated labor supply responses could simply be due to income effects. The parameterization in equation (3) does not allow for income effects, implying a vertical shift of the budget set will lead to the same labor supply. In Table 4, I control for income at zero earnings to allow for income effects. It might be important to control for each source of income at zero earnings, except AFDC/TANF and SNAP account for essentially all of the income for non-workers. Each column is analogous to those in Table 2. The sign on the total income at zero earnings is negative, as expected, small and marginally significant. A vertical shift in the budget set should lead to a lower labor supply. The inclusion of fixed effects
slightly reduces the elasticity estimates, but in a uniform way, suggesting income effects may be important, but are not driving the differences in labor supply responses across programs.

6 Policy Implications

In Section 5, I provided evidence that labor supply reacts to a greater degree to adjustments in work incentives derived from the tax code compared to changes in the (dis)incentives provided by welfare-type programs. In this section I will discuss what the findings mean in terms of policy.

I want to be clear about the limitations of the policy implications one can glean from the results in presented in Section 5. First I do not estimate the effect that changes to a program’s parameters have on the recipiency rate of the program. While effects on recipiency do not affect estimation of the elasticity of labor supply, it is important from an accounting standpoint, or for cost-benefit analysis. For example, if the benefit levels are increased for a particular program, the costs of the program increase for two reasons: directly from the increase in benefit levels for the current recipients, and indirectly due to an increase in recipients who now claim the benefit that did not prior to the increase. Second, the results in Section 5 are not sufficient to make claims about general equilibrium effects. Specifically an increase in benefits for a particular program or a decrease in taxes must be financed. To the extent that the burden of the financing derives from tax increases to married women, men, or higher educated individuals, the results in Section 5 describe an incomplete description of the effect of increasing transfers to single women. For example, suppose taxes
were increased on higher educated individuals to finance an increase in benefits to low income individuals. The results do not describe the change in labor supply for the higher educated due to higher taxes, which would be important to consider when designing policy.

Instead of providing a social welfare function, in this section I will highlight two potential policy goals and discuss what the above results suggest about attaining those goals.

**Policy Goal 1: Increase Employment/Decrease Non-employment**

Suppose the goal of the social planner is to induce non-employed to seek employment among those with low earnings potential. The social planner has two options: decrease transfers to the non-employed or increase transfers to low income workers.

First consider reducing transfers to the non-employed. Implementing this policy through the tax code is likely not feasible, the tax code currently provides no resources to the non-employed so reducing aggregate transfers would take the form of tax liability on those who have no earnings. Alternatively the planner could reduce benefits from welfare-type programs to the non-employed. Given the estimates from Section 5 one would expect the labor supply response from this type of measure to be relatively small and at the expense of the utility of the recipients of the transfers. However decreasing the benefits would not require any outside financing, and in fact would save government resources.

Suppose instead the social planner decided to increase benefits for low wage workers. This policy could be implemented through an EITC expan-
sion/income tax reduction or through a reduction in the phase out rate of TANF or SNAP. My estimates suggest that increases to EITC and other tax parameters would induce more people to seek employment than an equivalent phase-out rate adjustment to the welfare-type programs.

Policy Goal 2: Transfer Resources to Non-employed

Suppose the goal of the social planner is instead to transfer resources to the non-employed while minimizing distortion to the labor market. The social planner again has at least two options: increase the benefits to the non-employed or shift the entire budget set upwards.

Increasing the benefits to the non-employed could be accomplished through the tax code. While there are currently no refundable tax credits to those with no earnings, it seems more feasible to extend tax credits to the non-employed than to levy taxes. However, my estimates suggest that increasing benefits in the tax code would lead to a relatively large labor supply reduction. An increase in the benefits through the welfare-type programs, on the other hand, would elicit a smaller reduction in labor supply. However, since the recipiency rates of TANF and SNAP is smaller than that of the EITC, a welfare-type benefit increase would reach fewer individuals.

Alternatively the social planner could increase transfers to low income workers as well as the non-employed. This could be done through either the tax code or welfare-type programs. The benefit of this policy is that it would minimize the reduction in labor supply, as suggested by the estimates of the income effect in Table 4. The drawback of this policy option is,
of course, that it is the most costly of the options facing the social planner.

One takeaway is that US policymakers implemented policy in a manner consistent with the analysis of the two objectives above. AFDC and SNAP were largely designed to transfer resources to low or no income families. The institutional framework surrounding these programs limited the distortionary effect on the labor market as evidenced by the estimates in section 5. On the other hand, the EITC was designed with the goal of increasing labor supply. The larger labor supply elasticity is consistent with this type of program’s effectiveness.

7 Conclusion

In this paper, I consider four major sources of income support: federal taxes and credits, state taxes and credits, AFDC/TANF and SNAP. I separately and simultaneously estimate the labor supply effects of multiple overlapping income support programs. Using a simulated instrument strategy, I identify labor supply responses solely off of policy changes. I estimate that the labor force response to changes in the benefits administered through the tax code is larger than the response to changes in more traditional welfare programs like AFDC, TANF and SNAP. The differential responses suggest that the budget set faced by the labor force is more than just the sum of its parts. Identical budget sets comprised of different underlying programs can lead to different labor supply and welfare outcomes. Many models of taxation optimize the shape of the aggregate budget with estimates of the labor supply elasticity without independent consideration of the underlying programs. The estimates of this paper suggest that ac-
counting for the differences in elasticities across programs is important.

There are several limitations to the analysis that should be addressed in future work. Capturing all of the elements of the income support programs is challenging, especially after the 1996 welfare reform, and few empirical papers have attempted to do so. Including more of the state level policy variation may prove important. Analysis of labor response along the intensive margin could provide a more complete description of how the labor force responses to income programs. Finally, a theoretical model of taxation that considered multiple programs each with different labor supply responses could help explain how the results of this paper affect optimal policy.
Figure 1: EITC Benefits

Single Mother, 2 Children

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Notes: Each line describes the federal earned income tax credit for a different year.
Figure 2: Maximum EITC Benefits

![Graph showing maximum EITC benefits over time for different family sizes.]

**Notes:** Each line describes the federal Earned Income Tax Credit for an individual whose earned income qualifies them for the maximum benefit level.

Figure 3: State EITC Implementation

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Notes: This AFDC schedule assumes the single mother is both eligible and has no income other than wage earnings. Parameters of the schedule represent the AFDC rules faced when initially entering the program. The income disregards decrease after sustained earnings.
Figure 5: Example TANF Schedules

(a) California

(b) Delaware
Notes: These TANF schedules assume the single mother is both eligible and has no income other than wage earnings. Parameters of the schedule represent the TANF rules faced when initially entering the program. In some cases income disregards decrease after a period sustained earnings.
Figure 6: Example Aggregate Budget Sets

(a) Ohio 1992

(b) Ohio 1995
Notes: These budget sets assume the single mother has two children and is both eligible for AFDC/TANF and SNAP and has no income other than wage earnings. Parameters of the schedule represent the TANF rules faced when initially entering the program. In some cases income disregards decrease after a period sustained earnings. See Section 5.1 for more details.
Figure 7: Identifying Variation in Simulated Instrument

(a) Federal Taxes: Cross Child

Variation in Simulated Instrument for Change in Federal Tax Work Incentive

(b) Federal Taxes: Cross State

Variation in Simulated Instrument for Change in Federal Tax Work Incentive
Chagne in State Tax Work Incentive

Survey year

No Children
1 Child
2 Children
3 Children

Variation in Simluated Instrument for Change in State Tax Work Incentive

(c) State Taxes: Cross Child

Variation in Simluated Instrument for Change in State Tax Work Incentive

Survey year

California
Florida
Georgia
Illinois
Michigan
New Jersey
New York
North Carolina
Ohio
Pennsylvania
Texas
Virginia

(d) State Taxes: Cross State
Notes: Each of these graphs display the evolution of simulated instruments over time. These graphs show the values for high school dropouts. The left panels separate the values by number of children. The right panels separate by state and are shown for single mothers with two children. The value of the instrument is the increase in income by becoming employed. The vertical axis is denominated in thousands of real 2010 USD.
Table 1: Summary Statistics of Simulated Instrument

<table>
<thead>
<tr>
<th>Panel A: Demographics</th>
<th>(1) Estimate</th>
<th>(2) High School Dropout</th>
<th>(3) High School Graduate</th>
<th>(4) Some College</th>
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<tr>
<td>Age</td>
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<td>33.6</td>
<td>33.9</td>
<td>34.5</td>
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<tr>
<td>No Children Percent</td>
<td>65.1</td>
<td>59.6</td>
<td>65.8</td>
<td>67.0</td>
</tr>
<tr>
<td>1 Child Percent</td>
<td>17.7</td>
<td>16.9</td>
<td>17.8</td>
<td>18.0</td>
</tr>
<tr>
<td>2 Children Percent</td>
<td>10.8</td>
<td>12.3</td>
<td>10.6</td>
<td>10.3</td>
</tr>
<tr>
<td>3+ Children Percent</td>
<td>6.3</td>
<td>11.2</td>
<td>5.8</td>
<td>4.7</td>
</tr>
<tr>
<td>Percent Black</td>
<td>21.0</td>
<td>24.7</td>
<td>21.5</td>
<td>18.7</td>
</tr>
<tr>
<td>Percent Hispanic</td>
<td>14.6</td>
<td>30.0</td>
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<td>10.0</td>
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</table>

<table>
<thead>
<tr>
<th>Panel B: Income, Taxes and Transfers (Real 2010 Dollars)</th>
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<tbody>
<tr>
<td>Imputed Pre-tax Wage Earnings</td>
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<tr>
<td>Federal Taxes: No Children</td>
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<tr>
<td>Federal Taxes: 2 Children</td>
</tr>
<tr>
<td>State Taxes: No Children</td>
</tr>
<tr>
<td>State Taxes: 2 Children</td>
</tr>
<tr>
<td>AFDC/TANF: No Children</td>
</tr>
<tr>
<td>AFDC/TANF: 2 Children</td>
</tr>
<tr>
<td>SNAP: No Children</td>
</tr>
<tr>
<td>SNAP: 2 Children</td>
</tr>
<tr>
<td>AFDC/TANF and SNAP: Zero Income, No Children</td>
</tr>
<tr>
<td>AFDC/TANF and SNAP: Zero Income, 2 Children</td>
</tr>
<tr>
<td>Net Tax and Transfers ($T_i$): No Children</td>
</tr>
<tr>
<td>Net Tax and Transfers ($T_i$): 2 Children</td>
</tr>
</tbody>
</table>

Number of observations: 773367, 138766, 334359, 300242

Notes: This table summarizes the simulated instrument. Each of the tax and transfer variables are an average over a constant earnings distribution. The Imputed Pre-tax Wage Earnings is the weighted mean of the imputed incomes. A negative tax value is a tax credit. See Section 4.2 for details on the construction of the simulated instrument.
Table 2: Marginal Effects: Income Gain from Employment, Multiple Sources

<table>
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<tr>
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<th>(1)</th>
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<tbody>
<tr>
<td>( \Delta y ): Total Income</td>
<td>0.021</td>
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</tr>
<tr>
<td></td>
<td>(0.0024)**</td>
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<tr>
<td>( \Delta y ): Federal Taxes</td>
<td>0.045</td>
<td>0.041</td>
<td>0.038</td>
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<tr>
<td></td>
<td>(0.0052)**</td>
<td>(0.0047)**</td>
<td>(0.0053)**</td>
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</tr>
<tr>
<td>( \Delta y ): State Taxes</td>
<td>0.039</td>
<td>0.032</td>
<td>0.031</td>
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<tr>
<td></td>
<td>(0.018)**</td>
<td>(0.015)**</td>
<td>(0.015)**</td>
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<tr>
<td>( \Delta y ): AFDC/TANF</td>
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<tr>
<td></td>
<td>(0.0027)**</td>
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<tr>
<td>( \Delta y ): AFDC/TANF and SNAP</td>
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<td>0.020</td>
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<tr>
<td></td>
<td>(0.0024)**</td>
<td>(0.0025)**</td>
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<td>( \Delta y ): TANF and SNAP</td>
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<td>CraggDonald_F</td>
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Notes: (* P<.1, ** P<.05, *** P<.01). Standard errors clustered at the state level. The unit of observation is a state-year-educationGroup-numberKids cell. Regressions control for race, ethnicity as well as education, state, year and number of children fixed effects. Column 2 includes controls for SNAP. Column 3 estimates the joint effect of AFDC/TANF and SNAP, in addition to taxes. Column 4 introduces a dummy equal to one for every year after TANF was implemented in 1997. The fifth row of Column 4 is the estimate for AFDC and SNAP, the sum of the fifth and sixth rows is the estimate for TANF and SNAP. Implied elasticities are calculated the percent change in the employment ratio as a percent change in total income due to a change in the labeled source. See Section for details. The Cragg-Donald F-stat is a test for weak instruments with multiple endogenous variables. The \( \chi^2 \) and p-values are from a test that all of the listed coefficients are equal.
Table 3: Marginal Effects: Income Gain from Employment, Multiple Sources: Robustness

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<tr>
<th></th>
<th>(1) Division FE</th>
<th>(2) State FE</th>
<th>(3) Region FE</th>
<th>(4) Div x Yr FE</th>
<th>(5) St x Yr FE</th>
<th>(6) Reg x Yr FE</th>
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<tr>
<td>Δ y: Federal Taxes</td>
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<td>0.037</td>
<td>0.039</td>
<td>0.040</td>
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<td>(0.0053)***</td>
<td>(0.0051)***</td>
<td>(0.0053)***</td>
<td>(0.0056)***</td>
<td>(0.0059)***</td>
<td>(0.0053)***</td>
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<td>Δ y: State Taxes</td>
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<td></td>
<td>(0.015)**</td>
<td>(0.014)</td>
<td>(0.015)*</td>
<td>(0.015)*</td>
<td>(0.016)**</td>
<td>(0.016)*</td>
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<tr>
<td>Δ y: AFDC and SNAP</td>
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<tr>
<td>Δ y: TANF and SNAP</td>
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N: 16605
r2: 0.30
fed_elast: 0.62
state_elast: 0.50
AFDC_TANF_SNAP_elast: 0.32

Notes: (* P<.1, ** P<.05, *** P<.01). Standard errors clustered at the state level. Column 1 is a reproduction of Table 2, Column 4, for comparison. Column 2 replaces CPS division fixed effects with state fixed effects. Column 3 replaces CPS division fixed effects with CPS region fixed effects. Column 4 replaces CPS division fixed effects with division x year fixed effects. Column 5 replaces CPS division fixed effects with state x year fixed effects. Column 6 replaces CPS division fixed effects with CPS region x year fixed effects.
Table 4: Marginal Effects: Income Gain from Employment, Multiple Sources

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Notes: (* P<.1, ** P<.05, *** P<.01). Standard errors clustered at the state level. This table is analogous to Table 2, with the inclusion of a variable for the income an individual would receive if they had not earnings. The unit of observation is a state-year-educationGroup-numberKids cell. Regressions control for race, ethnicity as well as education, state, year and number of children fixed effects. Column 2 includes controls for SNAP. Column 3 estimates the joint effect of AFDC/TANF and SNAP, in addition to taxes. Column 4 introduces a dummy equal to one for every year after TANF was implemented in 1997. The fifth row of Column 4 is the estimate for AFDC and SNAP, the sum of the fifth and sixth rows is the estimate for TANF and SNAP. Implied elasticities are calculated the percent change in the employment ratio as a percent change in total income due to a change in the labeled source. See Section for details. The Cragg-Donald F-stat is a test for weak instruments with multiple endogenous variables. The χ² and p-values are from a test that all of the listed coefficients are equal.
Part II

Optimal Income Taxation with Unemployment and Wage Responses: A Sufficient Statistics Approach (Joint work with Kory Kroft, Etienne Lehmann and Johannes Schmieder)

8 Introduction

Recent decades have witnessed a large shift in the U.S. tax and transfer system away from welfare towards in-work benefits. In particular, for single mothers, work incentives increased dramatically: welfare benefits were cut and time limits introduced, the Earned Income Tax Credit (EITC) was expanded and changes in Medicaid, job training programs and child care provision encouraged work. The shift away from programs featuring a Negative Income Tax (NIT) structure (lump-sum transfers to the non-employed with positive employment taxes) towards EITC-like programs (negative employment taxes at the bottom) is prevalent in other countries including Canada, France, South Korea and the U.K.

The literature evaluating these policy reforms largely views them as successful. For single mothers, the reforms sharply reduced welfare caseloads and increased labor force participation and income (Eissa and Liebman, 1996, Meyer and Rosenbaum, 2001b, Eissa and Hoynes, 2006, Gelber and Mitchell, 2012, Hoynes and Patel, 2015) and consumption levels (Meyer and Sullivan, 2004, 2008). Within an optimal income taxation framework, the various tax policy changes substantially improved welfare (Eissa, Kleven, and Kreiner, 2008). This is consistent with Saez (2002) who shows that the optimal income tax features an EITC-like structure at the bottom
of the income distribution when labor supply responses are primarily concentrated along the extensive margin relative to the intensive margin and the welfare weight on the working poor is greater than one.

Two important assumptions in Eissa, Kleven, and Kreiner (2008) and Saez (2002) are that all job-seekers find work and wages are fixed with respect to the tax system. The first assumption may be appropriate during the 1990s when the U.S. unemployment rate was falling and was very low, by historical standards, but may be less realistic in more recent periods where unemployment rates exceeded 10 percent. In fact, recent work by Bitler, Hoynes, and Kuka (2014) shows that for single women, the EITC does not provide much protection during economic downturns. Furthermore, even in a full employment economy, the assumption of fixed wages may be implausible (Rothstein, 2010). It is also worth noting that these assumptions rule out any labor market spillover effects of government policies. Since anyone can find a job at all times, there is no mechanism by which a boost to the labor force could “crowd out” job finding. Thus, these assumptions are at odds with the growing body of evidence that suggest, especially during times when unemployment is high, government policies may induce substantial spillover effects, particularly at the bottom end of the income distribution. It is desirable to have a theoretical framework that can account for the presence of these spillovers.

The goal of this paper is to relax the fixed wage and full employment assumptions and reassess whether the optimal income tax features an EITC-like structure at the bottom, as in Saez (2002). The paper makes two key contributions, one theoretical and one empirical. Theoretically,
we derive a sufficient statistics optimal tax formula in a general model that incorporates unemployment and wage responses to taxation. In the model, individuals can be out of work by choice ("non-participants") or by failing in their search to find a job ("unemployed"). This contrasts with Saez (2002) where all active individuals are effectively working. This addresses Mirrlees (1999) who writes that "a desire is to have a model in which unemployment can arise and persist for reasons other than a preference for leisure". Rather than specifying the full structure of the labor market, we pursue a sufficient statistics approach (Chetty, 2009) by allowing wages and the "conditional employment probability" - the fraction of participating individuals that are effectively working (i.e. one minus the unemployment rate) - to depend in a reduced-form way on taxes. Our theoretical results show that, for each labor market, the sufficient statistics to be estimated are:  

i) the microeconomic participation response with respect to taxation,  

ii) the macroeconomic participation response with respect to taxation and  

iii) the macroeconomic employment response with respect to taxation.  

Unlike micro responses, macro responses allow wages and conditional employment probabilities in each labor market to respond to a change in taxes. When we consider a restricted version of the model, whereby tax liabilities in one market do not affect wages, conditional employment probabilities, and labor supply in other occupations (what we label the "no-cross effects" model), we show that an EITC-like policy is optimal provided that the welfare weight on the working poor is larger than the ratio of the micro participation elasticity to the macro participation elasticities.

\[18\] For ease of exposition, we hereafter refer to microeconomic as "micro" and macroeconomic as "macro".
elasticity.\textsuperscript{19} When the micro and macro effects are equal, this collapses to the condition in Saez (2002). Thus, if the macro effect is less than the micro effect, as our empirical evidence suggests, the optimal policy is pushed more towards an NIT, relative to the benchmark case.

The intuition for why our optimal tax formula depends on macro employment responses and macro and micro participation responses is the following. In the absence of unemployment and wage responses, behavioral responses to taxation only matter through their effects on the government’s budget because they have no first-order effect on an individual’s objective by the envelope theorem (Saez, 2001, 2002). However, the latter argument does not apply to wage and unemployment responses because these responses are not directly chosen by individuals but rather are mediated at the market level.\textsuperscript{20} Since the social welfare function is assumed to depend only on expected utilities, market spillovers due to wage and unemployment responses matter only insofar as macro responses of expected utility to taxes differ from micro responses. Moreover, since participation decisions depend only on expected utilities as well, these market spillovers are entirely captured by the ratio of macro over micro participation responses. This is related to results in Kroft (2008) and Landais, Michaillat, and Saez (2015) who show that to evaluate optimal unemployment insurance (UI), it is important to estimate the ratio of the micro and

\textsuperscript{19}The no-cross effects model resembles the pure extensive model in Saez (2002), but additionally allows for unemployment and wage responses to changes in tax liabilities in the same occupation.

\textsuperscript{20}For example, higher taxes in one occupation may change equilibrium wages, and therefore labor demand of firms and the conditional employment probabilities that workers face. Such responses may also appear in occupations other than the one where the tax has changed. Moreover, the tax change may reduce the number of job seekers, thereby triggering search externalities.
macro take-up and duration elasticities in the presence of spillover effects, respectively.

The optimal tax formulas structure our empirical strategy which estimates the sufficient statistics that are inputs to the optimal tax formula using a standard quasi-experimental research design. Following most of the literature on labor supply responses to taxation, we focus on single women. The primary advantage is that this group is most likely to be at the margin of participating in the labor market and is thereby most affected by tax and transfer policies at the bottom of the income distribution, in particular the EITC. We adopt a "cell-based" approach and define labor markets on the basis of education (high school dropouts, high school graduates, some college but no degree, and college graduates), state and year. This largely mirrors the definition of labor markets in Rothstein (2010). To identify the micro participation response, we rely on expansions to the federal EITC which differentially affected single women with and without children. For the macro participation and employment responses, we rely on variation in state EITC levels, as well as variation in welfare benefits within states over time. To isolate purely exogenous variation in tax liabilities coming from policy reforms, we implement a simulated instruments approach similar in spirit to Currie and Gruber (1996) and Gruber and Saez (2002). Our instrumental variables (IV) estimates show that the micro participation elasticity, for the full sample of single women, is 0.63.

Our sample omits married women and men. Rothstein (2010) points out that the wages of similarly skilled single and married women substantially diverged in the 1990s. For this reason, it seems reasonable to assume they operate in distinct labor markets. For men on the other hand, to the extent that they are substitutable for single women, we will be understating the size of each labor market and overstating the changes in market-level average tax rates. These effects will tend to work in opposite directions.
This generally lines up with the range of estimates reported in the literature (Eissa, Kleven, and Kreiner, 2008). Our estimate of the macro participation and employment elasticity is 0.51. Finally, we estimate how these behavioral responses vary over the business cycle, proxied by the local unemployment rate, and we find suggestive evidence that the responses are lower in magnitude when the unemployment rate is relatively high, although our estimates are imprecisely estimated. We also find suggestive evidence that the ratio of the micro to macro participation responses increases during times of high unemployment.

As an illustration, we use our empirical estimates to implement our sufficient statistics formula and calibrate the optimal income tax. We demonstrate three key results. First, relative to the optimal tax schedule in Saez (2002), we find that since the macro participation response is less than the micro response, this moves the optimal schedule more towards an NIT-like tax schedule with a relatively larger lump sum payment to the non-employed combined with higher employment tax rates. Second, we show that calibrating our tax formula with smaller (employment and participation) macro responses has a much larger effect on the shape of the optimal tax profile (leading to a larger lump sum transfer and employment taxes), relative to calibrating the Saez (2002) formula with a smaller employment elasticity. This shows that it is misleading to simply calibrate existing tax formulas with macro employment elasticities, as standard intuition might suggest. Third, we use our empirical estimates of behavioral responses over the business cycle to show that during recessions, the opti-
mal income tax at the bottom shifts more towards an NIT-like structure.\textsuperscript{22}

The primary advantage of our sufficient statistics approach is its generality with respect to the underlying mechanisms. In particular, competitive models with fixed and flexible wages (Diamond, 1980, Saez, 2002, 2004, Choné and Laroque, 2005, 2011, Rothstein, 2010, Lee and Saez, 2012) and models with matching frictions (Hungerbühler, Lehmann, Parmentier, and Van der Linden, 2006, Landais, Michaillat, and Saez, 2015) are special cases of our sufficient statistics formula. To show the role of only allowing for flexible wages, we retrieve in the online appendix (provided in Section V) the competitive model with flexible wages when we assume that the conditional employment probability is either one (i.e., full employment) or does not respond to taxes (exogenous unemployment), and permit wages to respond to tax liabilities. Under the assumption that the production technology exhibits constant returns to scale (CRS) and workers are paid their marginal products, we show that the optimal tax formula exactly equals the tax formula in Saez (2002) where wages are fixed. Thus, only allowing for endogenous wages, but not endogenous unemployment, does not affect the optimal tax schedule. The other advantage of our tax formula is that it is exact and does not rely on any approximations. The disadvantage of our approach however is that analytical results about the precise shape of the optimal tax schedule are harder to obtain.

\textsuperscript{22}Interestingly, while governments have in general shifted away from NIT programs, in practice, transfers to the bottom get increased during recessions. For example, the U.S. significantly increased transfers to the non-employed through the Supplemental Nutrition Assistance Program (SNAP) during the Great Recession as part of the American Recovery and Reinvestment Act of 2009. This suggests that the shape of optimal income transfers at the bottom might depend on the strength of the labor market. Unfortunately, there is very little research on this question to help guide policymakers since current models by design do not allow for this possibility.
Our paper builds on and contributes to the literature on labor supply responses to taxation in three ways. First, many studies in the tax literature do not clarify whether labor supply responses correspond to micro or macro elasticities. An important exception is Rothstein (2010) and Leigh (2010) who consider labor demand and wage responses to the EITC in the U.S. Like Rothstein (2010), our empirical work emphasizes this important distinction. Additionally, we estimate micro and macro effects, which is necessary to implement our optimal tax formula, and we use a single method and the same sample.\textsuperscript{23} This avoids the concern that differences in micro and macro estimates are confounded by differences in methods and/or different samples. Second, our results clarify the importance of distinguishing between the effects of taxes on labor force participation and employment. Some studies use the labor force participation rate as the dependent variable (Gelber and Mitchell, 2012) while others use the employment rate (Meyer and Rosenbaum, 2001b). Our optimal tax formula indicates that it is important to estimate both participation and employment elasticities. Third, this study adds to the large literature evaluating the impact of the EITC expansions in the 1980s and 1990s by expanding the analysis horizon until the most recent years.\textsuperscript{24}

\textsuperscript{23}A recent study by Jäntti, Pirttilä, and Selin (2015) estimates micro and macro labor supply elasticities using cross-country data from the Luxembourg Income Study (LIS) along with a single estimator. We estimate the micro elasticity using micro data and control for market fixed effects. For the macro elasticity, we pool the data to the market level and control separately for year and state fixed effects. One can show that this approach is essentially equivalent to one that estimates both the micro and macro equation in a single regression.

\textsuperscript{24}One of the earliest papers in this tradition, Eissa and Liebman (1996) evaluate the expansion of the EITC in the Tax Reform Act of 1986 and find positive and significant participation effects, but no effect on hours of work. Meyer and Rosenbaum (2001b) exploit variation in the EITC up until 1996, controlling for changes to welfare (AFDC and food stamps), Medicaid, child care subsidies, and job training during this time period.
A number of recent papers have highlighted the distinction between micro and macro behavioral responses. The first paper to show that both are important for optimal policy is Landais, Michaillat, and Saez (2015), who consider a model of unemployment insurance (UI) with labor market spillovers and demonstrate that the optimal benefit level is a function of the gap between micro and macro unemployment duration elasticities. While our model is related in that it deals with spillover effects, the difference is that we consider multiple income groups of the labor market and focus on the optimal non-linear income tax; particularly, optimal transfers at the bottom of the income distribution. Landais, Michaillat, and Saez (2015) on the other hand have a single labor market and focus on the optimal UI benefit level and how this should vary over the business cycle. Nevertheless, the distinction that the micro elasticity refers to responses that hold the job-finding rate (conditional on search intensity) and wages constant, while the macro elasticity allows the job-finding rate to adjust to UI benefits, is very similar to the distinction we introduce in our model. Partly inspired by Landais, Michaillat, and Saez (2015), some recent papers have tried to empirically estimate macro and micro effects of UI benefits (e.g. Lalive, Landais, and Zweimüller, 2015) and job search assistance programs (e.g. Crépon, Duflo, Gurgand, Rathelot, and Zamora, 2013) on unemployment durations.\footnote{Gelber and Mitchell (2012) exploit the same reform along with a large reform to the EITC in 1993 to examine the impact of taxes on the labor force participation of single women and their allocation of time to market work versus home production.} \footnote{Crépon, Duflo, Gurgand, Rathelot, and Zamora (2013) evaluate an experiment of job placement assistance and find evidence of negative spillover effects (i.e., crowd-out onto untreated individuals). They find evidence that these spillover effects are larger when the labor market is slack and interpret this evidence as consistent with a model of job rationing (Landais, Michaillat, and Saez, 2015). Lalive, Landais, and Zweimüller (2015)
The distinction between micro and macro responses also plays an important role in the recent literature estimating extensive and intensive labor supply responses (See Chetty, Guren, Manoli, and Weber, 2011, and Chetty, Guren, Manoli, and Weber, 2012, for an overview). The terms micro and macro responses in these papers correspond to conceptually the same responses that are identified using different sources of variation in taxes. For macro, the source of variation is cross-country or business cycle whereas for micro, the source of variation is quasi-experimental. Differences between the two have been attributed to adjustment costs (Chetty, Friedman, Olsen, and Pistaferri, 2011) and optimization frictions (Chetty, 2012), an issue we abstract from in this paper. Instead, we consider responses that do (macro) or do not (micro) allow for certain equilibrium adjustment mechanisms.

This paper also relates to recent research on whether the generosity of UI benefits should depend on the state of the labor market. Unemployment benefits create a similar problem as traditional welfare benefits in that they provide transfers that are conditional on not working (or at least are at their maximum) and thus provide incentives not to work, while at the same time providing important insurance against hardship. Just as in the optimal taxation literature, the efficiency loss from providing UI is inversely related to the labor supply elasticities. Baily (1978), Chetty (2006), Schmieder, Von Wachter, and Bender (2012), Kroft and Notowidigdo (2014) show that the unemployment spells of individuals ineligible for UI were affected by a large expansion of Austria’s UI benefits. Hagedorn, Karahan, Manovskii, and Mitman (2013) estimate large macro effects of unemployment insurance policies during the Great Recession. This is inconsistent with evidence that the micro effects of UI are small (Rothstein, 2011, Farber and Valletta, 2013). The authors stress the role of labor demand, although Marinescu (2014) does not find robust evidence of UI on vacancy creation.
and Landais, Michaillat, and Saez (2015) derive welfare formulas where the marginal effect of increasing the generosity of unemployment benefits depends on the elasticity of unemployment durations with respect to the benefit generosity. These papers provide empirical evidence that the labor supply elasticities determining the optimal benefit durations (Schmieder, Von Wachter, and Bender, 2012) and levels (Kroft and Notowidigdo 2014 and Landais, Michaillat, and Saez 2015) decline during periods of high unemployment and that the generosity of the UI system should therefore increase during these times. There are also papers that directly examine how labor supply responses to taxation vary with local labor market conditions. Closer to our setting, Herbst (2008) shows that the labor supply responses to a broad set of social policy reforms in the U.S. during the 1990s, such as EITC expansions, time limits, work requirements and Medicaid, are cyclical. Mogstad and Pronzato (2012) shows that labor supply responses to a “welfare to work” reform in Norway are attenuated when the local unemployment rate is relatively high.

Finally, our work broadly relates to research which permits labor demand variables to determine employment outcomes and welfare participation for males and females. Blundell, Ham, and Meghir (1987) shows that demand characteristics, such as unemployment rates, are important determinants of work for married females. Using the PSID, Ham and Reilly (2002) also find evidence that unemployment rates are significant predictors of work for males. While these papers focus on how demand-side factors affect the level of employment, our research explores whether such factors influence the change in employment in response to taxes and
transfers. The role of demand side factors in affecting welfare use has been noted by others (see Hoynes 2000), yet their normative implications have not been fully investigated so far.

The rest of the paper proceeds as follows. Section 20 develops our theoretical model. Section 10 contains details on Institutional background and describes our data and empirical results. Section 11 considers the policy implications of our theoretical and empirical findings. The last section concludes.

9 The theoretical model

In this section, we derive an optimal tax formula in a general model that is consistent with a rich set of labor market responses to taxation. Following Chetty (2009), we use this benchmark model to identify the sufficient statistics that are necessary to compute the optimal income tax. We do so first in the no-cross effects case where employment and participation responses are only on the extensive margin. This allows us to show the intuition of the main result before we go to the general formula that holds with arbitrary responses to taxes across labor markets. Our approach contrasts with papers that have incorporated unemployment into models of optimal taxation in a more structural way such as competitive models without unemployment (Mirrlees, 1971, Diamond, 1980, Saez, 2002), models with wage rigidity and job rationing (Lee and Saez, 2012) and matching models and Nash bargaining (Pissarides, 1985).\footnote{See Boadway and Tremblay (2013) for an excellent review of optimal income taxation in models with unemployment.}
we illustrate how these various structural models map into our sufficient statistic formula.

9.1 Setup

Labor markets

We generalize the model in the appendix of Saez (2002) by introducing unemployment and wage responses to taxation. The size of the population is normalized to 1. There are $I + 1$ “occupations” or income levels, indexed by $i \in \{0, 1, \ldots, I\}$. Occupation 0 corresponds to non-employment. All other occupations correspond to a specific labor market where the gross wage is $w_i$, the net wage (or consumption) is $c_i$ and the tax liability is $T_i = w_i - c_i$.

The assumption of a finite number of occupations is made for tractability. It is not restrictive as the case of a continuous wage distribution can be approximated by increasing the number $I$ of occupations to infinity. The timing of our static model is:

1. The government chooses the tax policy.

2. Each individual $m$ chooses the occupation $i \in \{0, \ldots, I\}$ to participate in. Individual heterogeneity only enters the model through the cost of search, as we indicate below.

3. For each labor market $i \in \{1, \ldots, I\}$, only a fraction $p_i \in (0, 1]$ of participants are employed, receive gross wage $w_i$, pay tax $T_i$ and consume the after-tax wage $c_i = w_i - T_i$. The remaining fraction $1 - p_i$ of participants are unemployed.
Unlike Saez (2002), we make a distinction among the non-employed individuals between the unemployed who search for a job in a specific labor market and fail to find one and the non-participants who choose not to search for a job.\footnote{We simply assume job search intensity is either zero for non-participants or one for participants. Introducing a continuous job search intensity decisions as Landais, Michaillat, and Saez (2015) would add notational complexity while not substantially modifying the results.} For each labor market \( i \in \{1, \ldots, I\} \), \( k_i \) denotes the number of participants, \( p_i \in (0,1] \) denotes the fraction of them who find a job and are working, hereafter the \textit{conditional employment probability}, and \( h_i = k_i p_i \) denotes the number of employed workers. The number of unemployed individuals in labor market \( i \) is \( k_i - h_i = k_i (1 - p_i) \) and the unemployment rate is \( 1 - p_i \). The number of non-participants is \( k_0 \). The number of non-employed is \( h_0 = k_0 + \sum_{i=1}^{I} k_i (1 - p_i) \).

All the non-employed, whether non-participants or unemployed, receive the same welfare benefit denoted \( b \).\footnote{This is because the informational structure of our static model prevents benefits from being history-dependent. Moreover, as the government only observes income, it cannot distinguish non-participants from unemployed individuals. This latter assumption seems more realistic than the polar opposite one where the government can perfectly monitor job search. In this case, and if there is only one occupation, the government can provide full insurance to the unemployed.} Therefore, the policy choice of the government is represented by the vector \( t = (T_1, \ldots, T_I, b)' \). The government faces the following budget constraint:

\[
\sum_{i=1}^{I} T_i h_i = b h_0 + E \iff \sum_{i=1}^{I} (T_i + b) h_i = b + E
\]  (6)

where \( E \geq 0 \) is an exogenous amount of public expenditures. One more employed worker in occupation \( i \) increases the government’s revenues by the amount \( T_i \) of tax liability she pays, plus the amount of welfare benefit \( b \).
she no longer receives, the sum of two defining the *employment tax.*\(^{29}\) The budget constraint states that the sum of employment tax liabilities \(T_i + b\) collected on all employed workers in all occupations finances the public good plus a lump-sum rebate \(b\) over all individuals.

Rather than specify the micro-foundations of the labor market, we use reduced-forms to describe the general equilibrium or *macro* responses of wages and conditional employment probabilities to tax policy \(t.\)\(^{30}\) In labor market \(i\), the gross wage is given by \(w_i = \mathcal{W}_i(t)\), the net wage is given by \(c_i = \mathcal{C}_i(t) \equiv \mathcal{W}_i(t) - T_i\) and the conditional employment probability is given by \(p_i = \mathcal{P}_i(t)\). At this general stage, we are agnostic about the micro-foundations that lie behind these macro response functions and we only assume that these functions are differentiable, that \(\mathcal{P}(\cdot)\) takes values in \((0,1]\) and that \(0 < b < \mathcal{W}_1(t) < \ldots < \mathcal{W}_i(t)\) for all tax policies \(t\). The latter assumption ensures that occupations indexed with a higher \(i\) correspond to labor markets with higher skills. The functions \(\mathcal{W}_i(\cdot), \mathcal{C}_i(\cdot)\) and \(\mathcal{P}_i(\cdot)\) encapsulate all the effects of taxes, including those occurring through labor demand and wage setting responses.

Profits do not appear explicitly in our model. This is consistent with two possible scenarios. First, many natural models of the labor market, such as competitive models with constant returns to scale (Lee and Saez, 2012) or models with matching frictions on the labor market and free entry

\(^{29}\)The literature uses instead the terminology *participation tax*, which we find confusing whenever unemployment is introduced. The *employment tax* \(T_i + b\) captures the change in tax revenue for each additional *employed* worker. An additional *participant* being only employed with probability \(p_i\), the change in tax revenue for each additional participant is only \((T_i + b)p_i\), which should correspond to the *participation tax*.

\(^{30}\)We implicitly assume that an equilibrium exists and is unique. This equilibrium varies smoothly with the policy \(t\) in a way described by the \(\mathcal{W}(\cdot), \mathcal{C}(\cdot)\) and the \(\mathcal{P}(\cdot)\) functions.
(Mortensen and Pissarides, 1999) have profits equal to zero in equilibrium. Second, our results are consistent with the presence of profits if we assume that profits are not taxed and if the welfare of capital owners who receive profits does not enter the social welfare function. These assumptions are clearly simplifying. We consider in subsection 9.4 an extension of our model with partially taxed profits.

**Labor supply decisions**

The structure of labor supply is as follows. We let \( u(\cdot) \) be the cardinal representation of the utility individuals derive from consumption. This function is assumed to be increasing and weakly concave. Individual \( m \) faces an additional utility cost \( d_i \) for working in occupation \( i \) and a utility cost \( \chi_i(m) \) for searching a job in labor market \( i \).\(^{31}\) Individual \( m \) thus enjoys a utility level equal to \( u(c_i) - d_i - \chi_i(m) \) if she finds a job in labor market \( i \), equal to \( u(b) - \chi_i(m) \) if she is unemployed in labor market \( i \), and \( u(b) \) if she chooses not to search for a job. Let \( \mathcal{U}_i(t) \overset{\text{def}}{=} \mathcal{P}_i(t) \left( u(C_i(t)) - d_i \right) + (1 - \mathcal{P}_i(t)) u(b) \) denote the gross expected utility of searching for a job in occupation \( i \), absent any participation cost, as a function of the tax policy \( t \), and let \( U_i \) denote its realization at a particular point of the tax system.\(^{32}\) Let \( U_0 = u(b) \) be the utility expected out of the labor force.

Individual \( m \) expects utility \( U_i - \chi_i(m) \) by searching for a job in labor market \( i \). She chooses to search in labor market \( i \) if and only if \( U_i - \chi_i(m) \)

---

\(^{31}\)We denote \( \chi_0(m) = 0 \). We furthermore assume that \( \chi_i(m) = +\infty \) if individual \( m \) does not have the required skill to work in occupation \( i \).

\(^{32}\)\( U_i \) is identical across all participants because the conditional employment probability \( p_i \) and the wage \( w_i \) are identical across participants in labor market \( i \) and in particular do not vary with \( (\chi_1(m), ..., \chi_I(m)) \).
\( \chi_i(m) > U_j - \chi_j(m) \) for all \( j \in \{0, ..., I\} \setminus \{i\} \). The set of individuals choosing to participate in labor market \( i \) is therefore \( M_i(U_1, ..., U_I, u(b)) \overset{\text{def}}{=} \{ m | i = \arg \max_{j \in \{0, ..., I\}} U_j - \chi_j(m) \} \). Assuming that participation costs \( (\chi_1, ..., \chi_I) \) are distributed in the population in a sufficiently smooth way and denoting \( \mu(.) \) the distribution of individuals, the number \( k_i \) of participants in labor market \( i \) is a continuously differentiable function of expected utility in each occupation through: \( k_i = \hat{K}_i(U_1, ..., U_I, u(b)) \overset{\text{def}}{=} \mu(M_i(U_1, ..., U_I, u(b))) \).

Participation decisions are determined through:

\[
    k_i \equiv K_i(t) \overset{\text{def}}{=} \hat{K}(\mathcal{U}_1(t), ..., \mathcal{U}_I(t), u(b))
\]

Finally, employment is given by:

\[
    h_i = \mathcal{H}_i(t) \overset{\text{def}}{=} K_i(t) \mathcal{P}_i(t)
\]

**Micro vs. Macro Responses**

A crucial distinction is the difference between macro and micro participation responses to taxes. We define the micro participation response to a tax change in the hypothetical case where tax changes do not affect gross wages \( w_1, ..., w_I \) or conditional employment probabilities \( p_1, ..., p_I \). This is, for instance, the case for tax reforms frequently considered in the microeconometric literature that affect only a small subset of the population, so that the equilibrium effects of the reform on wages and conditional employment probabilities can be safely ignored. The micro response of expected utility is thus \(-p_iu'(c_i)\). Moreover, from Equation (7), as taxes affect partici-
ipation decisions only through expected utility levels in each occupation, the micro participation response is given by:

$$\frac{\partial K_i}{\partial T_j} \overset{\text{Micro}}{\equiv} -p_j u'(c_j) \frac{\partial \hat{K}_i}{\partial U_j}$$  (9)

Conversely \textit{macro} responses encapsulates wage and conditional employment probability responses. The macro response of expected utility is therefore:

$$\frac{\partial U_i}{\partial T_j} = \left[ \frac{\partial \phi_i}{\partial T_j} + \frac{\partial \mathcal{P}_j u(c_j) - d_i - u(b)}{\partial T_j} \right] p_i u'(c_i)$$  (10)

The term within brackets on the right-hand side of (10) in particular describes how the wage and conditional employment probability responses induce a gap between macro and micro expected utility responses. Using (7) and (10), the macro participation response is given by:

$$\frac{\partial K_i}{\partial T_j} = \sum_{\ell=1}^{l} \frac{\partial \mathcal{U}_\ell}{\partial T_j} \frac{\partial \hat{K}_i}{\partial U_\ell} = \sum_{\ell=1}^{l} \left[ \frac{\partial \phi_\ell}{\partial T_j} + \frac{\partial \mathcal{P}_\ell u(c_\ell) - d_\ell - u(b)}{\partial T_j} \frac{p_\ell u'(c_\ell)}{p_\ell u'(c_\ell)} \right] p_\ell u'(c_\ell) \frac{\partial \hat{K}_i}{\partial U_\ell}$$  (11)

The micro and macro participation responses differ for two main reasons. First, utility levels in the occupation that experiences the tax change can be affected by change in the wage and in the conditional employment probability in that occupation, as we will discuss below. For micro responses, gross wages are held constant, thus \(\frac{\partial \phi_i}{\partial T_j} = -1\) and taxes are passed through one for one to the worker, while employment probabilities are also fixed and thus \(\frac{\partial \mathcal{P}_j}{\partial T_j} = 0\). For macro responses on the other hand, tax adjustments may affect gross wages in a variety of ways \(\frac{\partial \phi_i}{\partial T_j} \neq -1\) while employment probabilities may also change \(\frac{\partial \mathcal{P}_j}{\partial T_j} \neq 0\), e.g. due to changes
in labor supply in that occupation or due to changes in vacancy creation by employers, as we will discuss below. Second, utility levels can also be affected by change in the tax liability in other occupations, explaining the summation over all occupations in (11). This could be for example because increasing taxes in occupation \( j \) may lead firms to adjust their composition of labor inputs and may change labor demand for other occupations. Moreover, it may be because the workers who are less likely to search for jobs in occupation \( j \) may look for jobs in other occupations which will thus change equilibrium outcomes in those occupations.

**Social objective**

We assume that the government maximizes a weighted utilitarian welfare objective that depends only on individuals’ expected utilities:

\[
\Omega(U_1, \ldots, U_I, u(b)) = \int \gamma(m) \left( \max_i U_i - \chi_i(m) \right) d\mu(m) \quad (12)
\]

where the weights \( \gamma(m) \) may vary across individuals. In the particular case where the utility function \( u(\cdot) \) is linear, it is the variation of weights with the characteristics of individuals through the heterogeneity in \( \gamma(\cdot) \) that generates the social desire for redistribution, while if individual utility is concave the desire for redistribution comes (also) from individual risk aversion.\(^{33}\)

\(^{33}\)It is straightforward - and does not change our results below - to generalize this social welfare function to the case where the social planners maximizes an arbitrary concave function of individual expected utilities integrated over the population.
The optimal policy

The government chooses the tax policy $t = (T_1, \ldots, T_l, b)'$ to maximize (12) subject to the budget constraint (6). Let $\lambda > 0$ denote the Lagrange multiplier associated with the latter constraint. Following Saez (2001, 2002), we define the marginal social welfare weight of workers in occupation $i \in \{1, \ldots, l\}$ as:

$$g_i \overset{\text{def}}{=} \frac{1}{k_i} \frac{\partial \Omega}{\partial U_i} \frac{u'(c_i)}{\lambda} = \frac{p_i u'(c_i) \int_{m \in M_i} \gamma(m) \, d\mu(m)}{\lambda h_i}$$

(13)

The social weight $g_i$ represents the social value in monetary terms of transferring an additional dollar to an individual working in occupation $i$. It captures the micro effect on the social objective of a unit decrease in tax liability, expressed in monetary terms. Absent wages and conditional employment probabilities responses, the government is indifferent between giving one more dollar to an individual employed in labor market $i$ and $g_i$ more dollars of public funds. Using Equations (10) and (13), we get the following lemma (See Appendix 18).

**Lemma 1.** The first-order condition with respect to the tax liability $T_j$ in labor market $j$ is:

$$0 = h_j + \sum_{i=1}^l \frac{\partial \mathcal{H}_i}{\partial T_j} (T_i + b) + \sum_{i=1}^l \left[ \frac{\partial \mathcal{E}_i}{\partial T_j} + \frac{\partial \mathcal{P}_i}{\partial T_j} \frac{u(c_i) - d_i - u(b)}{p_i u'(c_i)} \right] g_i h_i$$

(14)

A unit increase in tax liability triggers the following effects:

1. **Mechanical effect**: Absent any behavioral response, a unit increase
in $T_j$ increases the government’s resources by the number $h_j$ of employed individuals in occupation $j$.

2. **Behavioral effects**: A unit increase in $T_j$ induces a change $\partial H_i / \partial T_j$ in the level of employment in occupation $i$. For each additional worker in occupation $i$, the government increases its resources by the employment tax $T_i + b$ that is equal to the additional tax received $T_i$ plus the benefit $b$ that is no longer paid.

3. **Social welfare effects**: A unit increase in $T_j$ affects the expected utility in occupation $i$ by $\partial \mathcal{U}_i / \partial T_j$. Multiplying by the rate $\frac{\partial \mathcal{O}_i}{\partial U_i} / \lambda$ at which each unit change in expected utility affects the social objective in monetary terms and using Equations (10) and (13), we get that the social welfare effect of tax $T_j$ in occupation $i$ is:

$$g_i h_i \left[ \frac{\partial \mathcal{O}_i}{\partial T_j} + \frac{\partial \mathcal{P}_i}{\partial T_j} \frac{u(c_i) - d_i - u(b)}{p_i u'(c_i)} \right].$$

Note that because the social welfare function depends on expected utility $U_i$, the labor supply response only modifies the decisions of individuals that are initially indifferent between two occupations, and thus only have second-order effects on the social welfare objective, by the envelope theorem (Saez, 2001, 2002). Conversely, wage and unemployment responses are general equilibrium (macro) responses induced by the market instead of being directly triggered by individual choices. This is the reason why these “market spillovers” show up in the social welfare effect through the term within brackets, unlike the participation responses. Because the social objective as well as participation decision depend on the tax policy only through expected utility levels in each occupation, the same terms $\frac{\partial \mathcal{O}_i}{\partial T_j} + \frac{\partial \mathcal{P}_i}{\partial T_j} \frac{u(c_i) - d_i - u(b)}{p_i u'(c_i)}$...
describe how macro social welfare effects differ from micro ones and how macro participation responses differ from micro ones.

**Optimal benefit level**

Finally, for the sake of completeness, the first-order condition with respect to the welfare benefit $b$ is (see Appendix 18):

$$0 = h_0 + \sum_{i=1}^{l}(T_i + b)\frac{\partial H_i}{\partial b} + g_0 h_0 + \sum_{i=1}^{l}g_i h_i \left[ \frac{\partial \kappa_i}{\partial b} + \frac{1}{p_i} \frac{\partial \mathcal{P}_i}{\partial b} \frac{u(c_i) - d_i - u(b)}{u'(c_i)} \right]$$  \hspace{1cm} (15)

where the social marginal welfare weight on the non-employed is:

$$g_0 \overset{\text{def}}{=} \frac{u'(b)}{h_0} \left[ \int_{m \in M_0} \frac{\gamma(m)}{\lambda} d\mu(m) + \sum_{i=1}^{l} \frac{g_i}{u'(c_i)} k_i (1 - p_i) \right]$$  \hspace{1cm} (16)

In particular, if we furthermore assume there is no income effects so that

$$\sum_{i=1}^{l} \frac{\partial \psi_i}{\partial T_j} = \frac{\partial \psi_i}{\partial b}, \quad \sum_{i=1}^{l} \frac{\partial \mathcal{P}_i}{\partial T_j} = \frac{\partial \mathcal{P}_i}{\partial b} \quad \text{and} \quad \sum_{i=1}^{l} \frac{\partial H_i}{\partial T_j} = \frac{\partial H_i}{\partial b},$$

we get that the weighted sum of social welfare weights is 1 (See Appendix 18):

$$g_0 h_0 + \sum_{i=1}^{l} g_i h_i = 1$$

### 9.2 The sufficient statistics optimal tax formula

To numerically implement the optimal tax formula in equation (14), one must know the gap in utilities between employment and non-employment, the responses of net wages to taxation $\frac{\partial \psi_i}{\partial T_j}$ and the responses of the conditional employment probabilities to taxation $\frac{\partial \mathcal{P}_i}{\partial T_j}$ that appear in the social welfare effects. We now show that there is a simpler representation for the optimal tax formula (14) in terms of the macro $\frac{\partial \kappa_i}{\partial T_j}$ and micro participation $\frac{\partial \mathcal{P}_i}{\partial T_j}$.
responses $\frac{\partial \hat{K}_{i}}{\partial T_{j}} \bigg|^{\text{Micro}}$. The advantage of this representation is that we may apply conventional econometric techniques to estimate these terms.

**The no-cross effect case**

To simplify the exposition and develop intuition, we begin with the “no-cross effect” case where we assume for simplicity that $\partial W_{i}/\partial T_{j} = \partial C_{i}/\partial T_{j} = \partial \mathcal{P}_{i}/\partial T_{j} = \partial \hat{K}_{i}/\partial U_{j} = 0$ for $i \neq j$ and $i \neq 0$. This means that labor demand only responds to tax liabilities in the same market, but not other markets. It also implies that labor supply responses are concentrated along the extensive margin; in other words, individuals can move from non-employment to work (or vice-versa) in a single occupation, but cannot move between occupations in response to a tax change. Thus, this rules out intensive margin responses. More precisely, we get from (10) that $\partial \mathcal{N}_{i}/\partial T_{j} = 0$, which together with (7) and (8) imply that: $\partial \mathcal{K}_{i}/\partial T_{j} = \partial \mathcal{H}_{i}/\partial T_{j} = 0$ for $i \neq j$, i.e. that the wage, the conditional employment probability, the employment level and the participation level in one occupation only depend on the welfare benefit $b$ and on the tax liability in the same occupation, and not on tax liabilities in the other occupations. The no-cross effect environment includes the model of Landais, Michaillat, and Saez (2015) where the wage depends on the level of tax liability but not on the marginal tax rate.

In the no-cross effect case, Equations (9) and (11) imply that we may express the macro participation response in terms of the micro participation response in the following way:

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34 This convention is similar to Saez (2002) who defines the extensive margin as the participation margin and the intensive margin as movements between occupations.
The formula (14) for the optimal tax liability in occupation $j$ then simplifies to:

$$0 = h_j + \left[ \frac{\partial C_j}{\partial T_j} + \frac{\partial \mathcal{P}_j}{\partial T_j} \frac{u'(c_j)}{p_j u'(c_j)} \right] \frac{\partial K_j}{\partial T_j} \bigg|_\text{Micro}$$

To better relate this expression to the optimal tax literature, we define the micro participation elasticity as $\pi_j^m \overset{\text{def}}{=} -\frac{c_j - b}{k_j} \frac{\partial K_j}{\partial T_j}$, which measures the percentage of employed workers in $i$ who leave the labor force when the tax liability is increased by 1 percent, holding wages and the conditional employment probabilities fixed. Next, we define the macro employment elasticity as $\eta_j \overset{\text{def}}{=} -\frac{c_j - b}{h_j} \frac{\partial \mathcal{H}_j}{\partial T_j}$. From (8), the macro employment response $\eta_j$ verifies $\eta_j = \frac{\partial \mathcal{P}_j}{\partial T_j} + \pi_j$. In particular, it encapsulates conditional employment responses $\frac{c_j - b}{p_j} \frac{\partial \mathcal{P}_j}{\partial T_j}$ in addition to the macro participation responses $\pi_j$. Moreover, wage and unemployment responses modify the macro participation responses $\pi_j$ from the micro ones $\pi_j^m$, as discussed above.

**Proposition 1.** The optimal tax formula in the no-cross effects case is:

$$\frac{T_j + b}{c_j - b} = 1 - \frac{\pi_j^m \delta_j}{\eta_j}$$

The no-cross effect environment is the simplest one to understand how the introduction of unemployment and wage responses modifies the opti-
mal tax formula compared to the pure extensive case without unemployment case considered by Diamond (1980), Saez (2002) and Choné and Laroque (2005, 2011) where it is: $\frac{T_j + b}{\eta_j} = \frac{1 - g_j}{\eta_j}$.

There are two key differences between Equation (18) and Equation (4) in Saez (2002). First, the denominator in (18) corresponds to the macro employment elasticity, whereas Saez (2002) does not distinguish between a micro employment elasticity and macro employment elasticity that includes all the general equilibrium effects of taxation. Second, equation (18) modifies the social marginal welfare weight by the ratio of the macro to micro participation elasticity. The response of expected utility may be different at the macro and micro levels. This is because the macro responses encapsulate not only the direct effect of a tax change on consumption, but also the indirect effects of a tax change on the wage $\frac{\partial W_i}{\partial T_i} \neq 0$ and on the conditional employment probability $\frac{\partial \varphi_i}{\partial T_i} \neq 0$. The ratio between the micro and macro expected utility responses corresponds exactly to the ratio of the macro to the micro participation elasticities. So the welfare effect may be larger or lower than the social welfare weight $g_i$. To understand why, consider a decrease in tax liability $T_j$. This triggers a positive direct impact on social welfare $-g_j h_j$, which is the only one at the micro level. Moreover, this decrease in tax liability typically induces a decreases in the gross wage when $\frac{\partial W_j}{\partial T_j} > 0$, so the responses of wage attenuates the direct impact on social welfare. Finally, the decrease in tax liability also typically triggers a rise in job creation, i.e. $\frac{\partial \varphi_j}{\partial T_j} < 0$, so the response of the conditional employment probability reinforces the direct impact on social welfare. The macro response of participation to taxation is therefore larger (smaller) than the
micro one if the impact of the conditional employment responses dominates (is dominated by) the impact of the wage responses. In particular, if the effect of the tax on the conditional employment probability happens only though a labor demand response, the macro participation response is higher than micro one if the labor demand elasticity is high enough. We therefore get:

**Corollary 1.** In the no-cross effect case, the optimal employment tax is negative whenever \( g_1 > \frac{\pi^m}{\pi^m} \).

According to (18), a negative employment tax (EITC) becomes optimal whenever the social welfare weight is higher than the ratio of micro over macro participation elasticity, instead of one without unemployment and wage responses.

**The case with cross effects**

We now turn back to the general formula with cross effects, where matrix notation turns out to be convenient. For \( f = \mathcal{K}, \mathcal{K}, \mathcal{H}, \mathcal{U}, \mathcal{P}, \mathcal{W} \) and \( x = T, U \), we denote \( \frac{df}{dx} \) the square matrix of rank \( I \) whose term in row \( j \) and column \( i \) is \( \frac{\partial f_i}{\partial x_j} \) for \( i, j \in \{1, \ldots, I\} \).\(^{35}\) Symmetrically, the matrix of micro responses are denoted \( \frac{df}{dx}\)\(^{\text{Micro}} \). Moreover, \( h = (h_1, \ldots, h_I)' \) denotes the vector of employment levels, \( gh = (g_1h_1, \ldots, g_Ih_I)' \) denotes the vector of welfare weights times employment levels and \( \cdot \) denotes the matrix product. Appendix 18.1 then shows that market spillover terms \( \frac{\partial C_i}{\partial T_j} + \frac{\partial P_i}{\partial T_j} \frac{u(c_i) - d_i - u(b)}{p_i u'(c_i)} \) that appear in the social welfare effects in the optimal tax formula (14) still

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\(^{35}\)In particular, these matrices do not include partial derivatives with respect to \( b \), nor do they include partial derivatives for occupation 0.
correspond to the ratio of macro over micro participation responses. The only difference is that in the presence of cross effects, this ratio should be understood in matrix terms. We thus get the following generalization of the optimal tax (17) in the presence of cross effects:

**Proposition 2.** If \( \frac{d\mathcal{K}^{\text{Micro}}}{dT} \) is invertible, the optimal tax system for occupations \( i = \{1, ..., I\} \) solves the following system of equations in matrix form:

\[
0 = h + \frac{d\mathcal{H}}{dT} \cdot (T + b) - \frac{d\mathcal{K}}{dT} \cdot \left( \left. \frac{d\mathcal{K}^{\text{Micro}}}{dT} \right| \right)^{-1} \cdot (g \ h) \tag{19}
\]

Equation (19) is expressed in terms of sufficient statistics. It implies that the ratio (in matrix terms) of macro to micro participation responses are the sufficient statistics to estimate, instead of the market spillover terms that depend on net wage \( \frac{\partial \mathcal{E}_i}{\partial T_j} \) and conditional employment probability responses \( \frac{\partial \mathcal{P}_i}{\partial T_j} \). Intuitively, because the social welfare function is assumed to depend only on expected utilities, the market spillovers that appear in the social welfare effects in (14) coincide with the terms \( \frac{\partial \mathcal{E}_i}{\partial T_j} + \frac{\partial \mathcal{P}_i}{\partial T_j} \frac{u(c_i) - d_i - u(b)}{p_i u'(c_i)} \) that describe how the macro responses of expected utility differ from the micro ones (see (10)). Moreover, because participation decisions depend only on expected utility as well, these market spillovers are entirely captured by the matrix ratio of macro over micro participation responses. Importantly, the gap between micro and macro responses does not matter for the behavioral effects, but only for the social welfare effects. This is because the matrix \( \frac{d\mathcal{H}}{dT} \) of macro employment responses already encapsulates the unemployment and wage responses in addition to the micro participation responses.
9.3 The links between the optimal tax formula and micro-foundations of the labor market

In this section, we discuss how different micro-foundations yield different predictions for the relative magnitude of micro and macro participation (and to a lesser degree employment) responses. This serves to build intuition for the macro-micro gap and thereby what economic forces push the optimal tax at the bottom towards an EITC or NIT, while at the same time highlighting how our framework encompasses standard models of the labor market. We start with the search-matching paradigm before presenting the job-rationing paradigm. We then briefly discuss the competitive model and finally models with a wage moderating effect of tax progressivity.

Search and matching models with constant returns to scale (CRS)

In its simplest version, the search-matching framework (Diamond, 1982, Pissarides, 1985, Mortensen and Pissarides, 1999, Pissarides, 2000) assumes a linear production function and a constant returns to scale matching function which gives the number of jobs created as a function of the number of vacancies and the number of job seekers. Firms employ more workers the lower the gross wage (which makes it more rewarding for firms to hire a worker) and the more numerous job-seekers there are (which decrease the search congestions from firms’ viewpoint thereby easing their recruitment). In the model, the conditional employment probability $p_i$ is a decreasing function $\mathcal{L}_i(\cdot)$ of the gross wage and is independent of the
number of job-seekers.\textsuperscript{36} Therefore, a policy reform that increases labor supply, without affecting the gross wage, leads to a rise in employment in the same proportion as the rise in labor supply, but does not affect the employment probability.

If we consider a version of the matching model where wages are fixed, then the conditional employment probabilities are fixed, so the macro participation responses are equal to the micro ones. If we instead consider a version of the matching model where wage setting is based on wage bargaining, taxes may affect the outside option for workers as well as the match surplus and thus equilibrium wages and in turn conditional employment probabilities. To build intuition, consider the case with risk neutral workers (hence $u(c) \equiv c$) and proportional bargaining. In such a setting, workers receive an exogenous share $\beta_i \in (0, 1)$ of the total match surplus $y_i - T_i - d_i - b$, so the wage is given by:\textsuperscript{37}

\begin{equation}
    w_i = \mathcal{W}_i(T_i, b) \equiv \beta_i y_i + (1 - \beta_i)(T_i + d_i + b)
\end{equation}

Combining the labor demand relation $p_i = \mathcal{L}_i(w_i)$ with the wage equation (20) and the assumption that labor supply responses are concentrated along the extensive margin provides a complete search-matching micro-foundation for the no-cross effect economy. The following proposition shows that the macro-micro participation gap is directly linked to the bargaining weights and the elasticity of the matching function with respect

\textsuperscript{36}We derive in Appendix19 this standard result, as well as the proof of Proposition 3 below.

\textsuperscript{37}A similar expression for wage bargaining appears in Jacquet, Lehmann, and Van der Linden (2014) and in Landais, Michaillat, and Saez (2015).
to the number of job-seekers \( \mu_i \in (0, 1) \):

**Proposition 3.** In the search-matching economy with proportional bargain-
ing (20), the micro and macro participation responses are equal either when
the workers have full bargaining power so there is no wage responses, or
when the Hosios (1990) condition \( \beta_i = \mu_i \) is verified. If \( \beta_i < \mu_i \) the macro
response is lower then micro one. If \( \mu_i < \beta_i < 1 \) the macro response is larger
then micro one.

An increase in tax liability has three effects on expected utility, thereby
on participation decisions. First, absent wage and conditional employ-
ment response, a rise in \( T_i \) has a direct negative impact at the micro level
(holding \( w_i \) and \( p_i \) constant) as it reduces the net wage and thus incen-
tives to work and to participate. Second, at the macro level, gross wages
increases (through bargaining) attenuating the direct labor supply effect.
Finally, the gross wage increase triggers a reduction in labor demand that
amplifies the direct effect at the macro level. If the workers get all of the
surplus (i.e. if \( \beta_i = 1 \)), wages do not respond to taxation \( \frac{\partial w_i}{\partial T_i} = 0 \), the con-
ditional employment probabilities are not affected so the micro and macro
responses to participation are identical. On the other hand, if \( \beta_i < 1 \), the
conditional employment probability effect dominates (is dominated by) the
wage effect whenever the labor demand elasticity is (not) sufficiently elas-
tic, which happens when the matching elasticity \( \mu_i \) is higher (lower) than
the bargaining share \( \beta_i \). Propositions 1 and 3 imply that the optimal em-
ployment tax rate on the working poor is more likely to be negative in the
no-cross effect DMP case than in the pure extensive case if the workers’
bargaining power is inefficiently high, i.e, is higher than the bargaining
power prescribed by the Hosios (1990) condition.\(^{38}\) Therefore, in the DMP model the macro micro participation gap can be higher or lower than one, attenuating or reinforcing the arguments in favor of a negative participation tax at the bottom.\(^{39}\)

Finally, it is worth noting that under the Hosios (1990) condition \(\hat{\beta}_i = \mu_i\), while the macro and the micro participation elasticities are equal, this does not imply that the macro employment elasticities is equal to the micro employment elasticity. At the micro level, for fixed wages and tightness, a 1% increase in tax reduces employment only through the reduction in participation. The micro employment elasticity is therefore equal to the micro participation elasticity. Under the Hosios (1990) condition, the latter is equal to the macro participation elasticity. However, as a 1% increase in tax also decreases tightness because of the wage response to taxes, the conditional employment probability is also reduced, so the macro employment response is larger than the macro participation response.

**Job-rationing models**

An older tradition in economics has proposed job rationing to explain unemployment. In contrast to the matching framework, the job-rationing framework assumes search frictions away and considers that each type of labor exhibits decreasing marginal productivity. In each labor market, \(^{38}\)As \(\frac{\pi_j}{\eta_j} = \frac{\beta_j}{\mu_j}\) from (29), Equation (18) becomes \(\frac{T_j + b}{\tau_j - b} = \frac{1}{\eta_j} \frac{\beta_j}{\mu_j} \frac{1}{\eta_j}\) which corresponds to (19b) in Jacquet, Lehmann, and Van der Linden (2014). \(^{39}\)By extending this model with intensive labor supply decision, the present model can include the central mechanism of Golosov, Maziero, and Menzio (2013) where firms have different productivity and individuals direct their search.
employment is determined by the equality between the marginal product and the wage. Unemployment occurs whenever the wage is set above its market-clearing level. This theory of unemployment that Keynes (1936) attributed to Pigou was formalized in the disequilibrium theory (Barro and Grossman, 1971) and further developed in models that allowed for wages being set endogenously above the market clearing level (McDonald and Solow, 1981, Shapiro and Stiglitz, 1984, Akerlof and Yellen, 1990).

To develop some intuition about the macro-micro participation gap in job-rationing models, we now consider a model with a single type of labor that exhibits a decreasing marginal productivity and a fixed gross wage $w$. This can occur for instance as a result of a minimum wage regulation. The fixed wage determines the level of employment $h$, independently of the number of participants. We assume that individuals who participate face a heterogeneous participation cost $c$ that is sunk upon participation. The $k$ participants face the same probability $p = h/k$ to be employed, whatever the participation cost $c$ they incur if they participate. In such a framework, a tax cut in $T$ triggers a rise in participation at the micro level. However, provided that this tax cut occurs for a fixed wage, employment does not change, so the macro employment response is nil. Therefore, as

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40 The Keynesian and New Keynesian theories of unemployment in addition assume nominal rigidities to give a transitional role to aggregate demand management policies. See also Michaillat and Saez (2015) for an extension of the new Keynesian model in which disequilibrium due to price rigidity are smoothed by matching functions on both the labor and the product market.

41 Note that with a fixed wage, it is no longer equivalent whether the firm or the worker pays the tax. If the firm pays the tax, then a tax cut reduces the cost of labor and increases labor demand. In this case, the government controls not only the total tax liability in an occupation, but also the cost of labor and thereby the employment level. Lee and Saez (2012) provides conditions where the government finds it optimal to set the cost of labor above the market-clearing level, thereby generating unemployment in a job-rationing model.
the number of participants increases, the probability to be employed is reduced, which attenuates the participation responses at the macro level, as compared to the micro one. As a result, the optimal employment tax on the working poor is more likely to be positive in this job-rationing model without cross effect than in the pure extensive case.

There are different job-rationing models in the literature. For instance, in Lee and Saez (2012), there are different types of labor that are perfect substitutes, the minimum wage policy is explicitly an additional policy instrument and efficient rationing is assumed, so that the probability to be employed varies across participants as a function of their private cost upon working. Wages can also be made endogenous through union bargaining (McDonald and Solow, 1981) or through efficiency wages (Shapiro and Stiglitz, 1984, Akerlof and Yellen, 1990). Job rationing can also be analyzed within a search-matching framework if decreasing returns to scale is assumed for the production function, as in Michaillat (2012). As in a job-rationing model without matching, the macro employment effect would be dampened compared to the micro one and conditional employment probabilities would fall in response to a tax decrease. This in turn generates a gap in the micro and macro participation response that captures the spillover effect on the labor market. While decreasing returns to scale may not be realistic in the long run, it may be plausible at least in the short-run during recessions with aggregate demand shortfalls. Landais, Michaillat, and Saez (2015) discuss this possibility as a possible reason that the effect of unemployment insurance benefits on employment may be larger when the labor market is tight than when it is slack and thus the moral haz-
ard associated with UI may be less severe during a crisis. For the same reason it may be that reductions in tax levels may have a larger effect on employment in recessions than in booms and the optimal policy during recessions may look more like an NIT.\textsuperscript{42}

**Competitive models**

Like job-rationing models, competitive models assume search frictions away. However, these models assume that in each labor market, the gross wage adjusts to clear the labor market so there is no unemployment. If, in addition, the technology exhibit constant returns to scale and perfect substitution across the different types of labor, labor demand is perfectly elastic and our model reduces immediately to Saez (2002).\textsuperscript{43} In such a model, there is no difference between macro and micro responses, so the optimal tax formula depends only on the macro (or micro) employment effect of taxes. On the other hand, consider a competitive model with a constant returns to scale technology and flexible wages: there would be no unemployment, but wages may adjust to taxes due to imperfect substitution across the different types of labor. In this case the micro and macro employment responses may be different due to the wage adjustments in each labor market, but the participation gap would still capture these spillover effects. Saez (2004) showed that in such a model, the optimal tax formula

\textsuperscript{42}Though note that we have a static framework which may not be well suited to determine time-varying optimal taxes over the business cycle.

\textsuperscript{43}Assuming fixed $w_i$ and $p_j$, equation (14) collapses to the optimal tax formula (11) in the Appendix of Saez (2002). This formula can be further specialized by assuming that labor supply responses are concentrated along the intensive margin (Mirrlees (1971) and Saez (2002, Equation (6))), along the extensive margin (Diamond (1980), Saez (2002, Equation (4)) and Choné and Laroque (2005, 2011)) or both (Saez (2002, Equation (8))))
can be expressed using only the micro employment response and takes the same form as Saez (2002). In the on-line Appendix, we show that this result remains valid if unemployment rates are positive but exogenous. So, the optimal employment tax is negative when the social marginal welfare weight exceeds one. However, even in this case, our optimal tax formula (19) remains valid.

**Wage moderating effects of tax progressivity**

Another strand in the literature has stressed the possibility that increases in tax progressivity may actually increase employment. For example in the monopoly union model, unions set the wage to maximize the expected utility of its members, which is increasing in the net wage and in the level of employment. Since the level of employment is decreasing in the gross wage, unions do not want to push the wage too high. If tax rates increase (become more progressive) the wedge between net and gross wages increases and therefore a one unit increase in the net wage will have to be traded off against a larger loss in employment. Thus unions may actually accept a lower gross wage in response to an increase in tax progressivity and tax increases may increase employment.

This result has been obtained in a Monopoly unions model with job rationing by Hersoug (1984), in a union bargaining model by Lockwood and Manning (1993) or in the competitive directed search model (or wage posting) of Moen (1997) by Lehmann, Parmentier, and Van der Linden (2011). A very similar result can also hold in the efficiency wage model of Pisauro (1991) or within the matching framework with Nash bargaining (Pissarides, 1985, 1998), or with the bargaining model of top income earners of Piketty, Saez, and Stantcheva (2014). Evidence for this wage moderating effect of tax progressivity can be found in Malcomson and Sartor (1987), Holmlund and Kolm (1995), Hansen, Pedersen, and Sløk (2000) and Brunello and Sonedda (2007), while Manning (1993) and Lehmann, Lucifora, Moriconi, and Van der Linden (2015) provide some empirical support for the unemployment reducing effect of tax progressivity.
introducing the wage moderating effect of tax progressivity into the model is to make the matrix $\frac{dW}{dT}$ and therefore the matrices $\frac{d\phi}{dT}$, $\frac{d\psi}{dT}$, $\frac{dK}{dT}$ and $\frac{dH}{dT}$ non-diagonal. The wage moderating effect of tax progressivity is therefore an argument against the no-cross effect restriction, which is different than the presence of labor supply responses along the intensive margin.\footnote{In the context of our framework reduced to the case with two occupations $I = 2$, these models imply that the wage functions $\psi_i$ not only verify $\frac{\partial \psi_i}{\partial T_2} > 0$ and $\frac{\partial \psi_i}{\partial T_1} > 0$, as in the proportional bargaining case, but also that the marginal tax rate, as approximated by $T_2 - T_1$, has a wage moderating and unemployment reducing effect. This implies that $\frac{\partial \phi_2}{\partial \tau_1} > 0 > \frac{\partial \phi_1}{\partial \tau_1}$. Within a matching model, using $p_i = \mathcal{L}_i(w_i)$, we obtain $\frac{\partial \phi_2}{\partial \tau_2} < 0$ and $\frac{\partial \phi_1}{\partial \tau_1} < 0$, but also $\frac{\partial \psi_2}{\partial \tau_1} < 0 < \frac{\partial \psi_1}{\partial \tau_1}$. Hence, making the tax schedule more progressive by increasing $T_2$ and decreasing $T_1$ increases employment in both occupations, which the government finds beneficial whenever employment taxes remain positive. Hence, compared to the proportional bargaining case, the case with a wage moderating/unemployment reducing effect of tax progressivity leads to a more progressive optimal tax schedule as formally shown by Hungerbühler, Lehmann, Parmentier, and Van der Linden (2006), Lehmann, Parmentier, and Van der Linden (2011).}

\section{The introduction of profits}

Up to now, profits did not appear in our model. We assumed that if firms make profits, these profits are untaxed and these profits are received by some "capital owners" whose welfare are not included in the social welfare function. Alternatively, the public finance literature considered a polar assumption where profits are assumed to be fully taxed, or, equivalently, where all production is controlled by the government (Diamond and Mirrlees, 1971). It is therefore important to consider an extension of our model where profits are taxed at an exogenous rate denoted $\tau$.

For that purpose, we consider a model where a representative firm produces a numeraire good using a decreasing returns to scale technology $F(h_1, \ldots, h_I)$. For simplicity, we consider a pure job rationing model with-
out search frictions on the labor market. Firms adjust their labor demand to maximize their profits and we get the labor demand conditions $F_i(h_1, \ldots, h_I) = w_i$ for all types of labor. With the additional tax revenues from corporates, the budget constraint (6) becomes:

$$\sum_{i=1}^{l} (T_i + b) h_i + \tau \left( F(h_1, \ldots, h_I) - \sum_{i=1}^{l} w_i h_i \right) = b + E$$

Using Hotelling’s lemma, the optimality condition is:

$$0 = h_j + \sum_{i=1}^{l} \frac{\partial H_i}{\partial T_j} (T_i + b) + \sum_{i=1}^{l} \left[ \frac{\partial e_i}{\partial T_j} + \frac{\partial \Phi_i}{\partial T_j} \left( u(c_i) - d_i - u(b) \right) \right] g_i h_i - \tau \sum_{i=1}^{l} \frac{\partial \psi_i}{\partial T_j} h_i$$

Compared to (14), a new term appears when profits can be taxed: a change in tax on labor of type $j$ may affect the wages on labor of type $j$ which triggers a change in the profit tax base. Assuming cross-effects away, the optimal tax formula (18) becomes:

$$\frac{T_j + b}{c_j - b} = \frac{1 - \frac{\pi_j}{\pi_j^m} g_j - \tau \frac{\partial \psi_j}{\partial T_j}}{\eta_j}$$

Under rigid wage, the formula with profits is therefore unchanged. If a part of the tax incidence is conversely on the firm side so that $\frac{\partial \psi_j}{\partial T_j} > 0$, then EITC becomes more desirable because it triggers a wage reduction that increases profits, thereby providing additional tax revenue whenever $\tau > 0$.

This extension with profits in a model with diminishing returns to scale is however partial equilibrium. Typically, one may consider that the actual
technology exhibits constant returns to scale once a fixed input is made explicit. The above analysis therefore assumes an exogenous supply of this fixed factor. While this may be reasonable for land, it is more disputable if one may think of physical or technological capital for which the supply is probably very elastic in the long run. Therefore, to include profit taxation, one needs to make explicit the supply of this input, which is clearly beyond the scope of the present paper.

10 Estimating Sufficient Statistics

To illustrate the practical relevance of our optimal tax formula, we estimate the sufficient statistics necessary to implement our optimal tax formula, namely the macro employment response to taxes, and the micro and macro participation responses. We follow the large empirical literature on the effects of the EITC and welfare reform in the U.S. and focus on single women throughout the last three decades. As a consequence of the gradual expansion of the EITC and the 1990’s welfare reform, this group experienced substantial changes in participation and marginal tax rates differentially by number of children, within and across states. These policy reforms provide sufficient variation to identify both micro and macro participation responses and macro employment responses.
10.1 Data

Current Population Survey (CPS)

Our analysis is based on data from the monthly outgoing rotation group (ORG) and the March annual data of the Current Population Survey (CPS). The March annual data spans the time period 1984-2011, while the ORG data (from IPUMS) spans 1994-2010. As our analysis sample, we select all single women age 18 to 55 who are not in the military or enrolled full time in school or college. Since there was insufficient tax variation for higher income individuals we furthermore restrict our sample to women with education less than a bachelors degree. Our theory distinguishes between individuals who choose to participate in the labor force (and are employed or unemployed) and those individuals who are actually employed. We measure these labor market states using the standard International Labor Office (ILO) criteria. A person is classified as being in the labor force if she is either employed or unemployed (i.e., actively looking for a job during the reference week and was available for work) and employed if she has been working during the reference week (or been temporarily absent from a job).

Panel A of Table 5 shows descriptive statistics for the demographic characteristics of single women in the March CPS for the full sample (Column 1) and broken down by educational attainment groups (Columns 2-4), pooling all years from 1984 to 2011. The age range is pretty similar.

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46 For complete details on sample construction and variable definitions, please see the online appendix (Section V).

47 We do not include the CPS ORG in this table since it spans different years, but when we compare sample means for the March CPS and ORG for the same period they are
across the three education groups - less than high school, high school, and some college - but there are large differences in the distribution of number of children, with lower educated single women being much more likely to be mothers. This is likely due to our sample restriction to single women since higher educated mothers are more likely to be married. Additionally, low educated women are more likely to be black or Hispanic than high educated ones. Panel B displays labor market variables by educational attainment. Lower educated women are much less likely to be in the labor force than higher educated ones and also experience higher unemployment rates.

**Tax and Transfer Calculator**

In order to estimate the employment and participation effects of taxes and transfers it is necessary to compute the budget sets that individuals face. For this purpose, we build a calculator that computes taxes and transfers at (nominal) income levels for single women, depending on the number of children, state and year.\(^{48}\) We assume that a woman is filing as the head of the household and claims her children as dependents. To compute taxes (covering federal and state income taxes, including tax credits, as well as FICA liability), we rely on the NBER TAXSIM software. We assign taxes based on state of residence, as reported in the CPS, as well as number of children, year, and income.\(^{49}\) To compute transfers,

\(^{48}\)We describe in details below how we impute income that serves as an input to the calculator.

\(^{49}\)For an individual who resides and works in different states, the following rules apply. Generally an individual is required to pay income tax to his or her state of residence first.
in particular Aid to Families with Dependent Children (AFDC), Temporary Assistance for Needy Families (TANF) and Supplemental Nutrition Assistance Program (SNAP), we construct a benefit calculator based on rules published in the Welfare Rules Database, managed by the Urban Institute. This allows us to compute the benefits an individual is eligible for, as a function of number of children, state of residence, year and income. The shift from AFDC to TANF introduced a number of additional work and eligibility requirements for welfare recipients. For example, federal rules require a minimum number of TANF recipients to be employed and the lifetime duration of receiving TANF benefits is limited to a total of 5 years.\footnote{In general, a state must have 50 percent of its single parent households and 90 percent of its dual parent households engaged in work-related activities (these include not only work but searching for work or training courses) for a minimum number of hours per week (30 hours per week or 20 hours if there is a young child). The 50 percent and 90 percent are calculated from a pool of “work-eligible individuals” which does not include single parents of children under the age of 1. States can obtain credits against the 50 and 90 percent rates for overall caseload reduction.}

Rather than incorporate all of these policies explicitly into our empirical framework, we multiply benefits by recipiency rates constructed from the Survey of Income and Program Participation (SIPP). The new eligibility requirements are reflected in lower observed recipiency rates in our sample post-welfare reform.

We use our tax and transfer calculator to compute the incentive to work. Since we focus solely on the extensive margin in our analysis, we capture work incentives using just two measures, the transfer an individual receives when she has zero income and the tax and transfer level at the

Then they must file as a non-resident in the state where they work, but get to take the amount of tax paid to the state of residence as a tax credit, and only pay the difference. If the amount of tax paid to the state of residence is greater than the tax bill for the work state, the individual doesn’t pay anything to the work state, but still has to file. We don’t take this into account in computing tax liabilities.

Rather than incorporate all of these policies explicitly into our empirical framework, we multiply benefits by recipiency rates constructed from the Survey of Income and Program Participation (SIPP). The new eligibility requirements are reflected in lower observed recipiency rates in our sample post-welfare reform.

We use our tax and transfer calculator to compute the incentive to work. Since we focus solely on the extensive margin in our analysis, we capture work incentives using just two measures, the transfer an individual receives when she has zero income and the tax and transfer level at the
earnings level an individual obtains when working. A key difficulty is that earnings, and hence tax liabilities, are unobserved for non-employed individuals. Moreover, earnings for employed workers may be endogenous to the tax system. We proceed using two approaches. First, we impute an individual’s tax liability following the approach taken in Eissa and Hoynes (2004) and Gelber and Mitchell (2012). We begin by running separate regressions for each education group \(e\) and year \(t\) of log annual earnings for individual \(m\) on state fixed effects \(\delta_{e,s,t}\) and control variables \(X_{m,e,s,t}\):

\[
\log(w_{m,e,s,t}) = \delta_{e,s,t} + X_{m,e,s,t}p_{e,t} + \epsilon_{m,e,s,t}
\]  

The control variables include state fixed effects, a quadratic function of age, dummy variables for black and hispanic, and a categorical variable describing geographic location (i.e., urban versus rural). For each individual in our sample (both the non-employed and employed), we construct predicted earnings using the regression coefficients estimated from our model. This is for the purpose of obtaining a consistent specification.\(^{51}\)

We then use predicted earnings to impute an individual’s tax liability using TAXSIM and the benefit calculator described above.\(^{52}\)

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\(^{51}\)For this exercise, we use earnings from the March CPS. To deal with misreporting we also drop observations where the implied hourly wage is less than one dollar or greater than one hundred dollars.

\(^{52}\)As an alternative, we tried performing a Heckman selection correction to control for self-selection using the number of children and the presence of young children in the selection equation. However, we found that the pattern of results were not very well behaved. In particular, predicted earnings for high school dropouts seemed too high and earnings for higher education levels seemed unrealistically low relative to the raw differences earnings across education groups. This is likely due to the lack of a convincing instrument for working.
In the online appendix (Section V), we present OLS regressions of participation and employment using this imputed tax liability. One problem with this approach is that the demographic distribution itself, and therefore the imputed tax liabilities, might be endogenous to tax policy. For instance, more generous transfers to single mothers with kids, but not to women without children, may boost fertility and impact earnings. To address this concern, we also rely on a simulated instrument approach based on Currie and Gruber (1996).\footnote{Gruber and Saez (2002) use this approach to estimate taxable income elasticities; however, we are not aware of any papers that use this approach to estimate extensive margin labor supply responses.} This approach isolates policy variation in tax liabilities since it uses a fixed income and demographic distribution during the sample period.

There are several steps that we take to implement this procedure. To construct the simulated micro tax liabilities, we first compute real earnings in 2010 dollars for each employed individual in the sample. Second, using earnings for the full sample of employed individuals across all years 1984-2011, we construct the percentiles of the empirical earnings distribution. Third, we compute for each education group, the percentage of workers that fall into each centile across all states and years. Fourth, for each year, we compute the nominal earnings level in each centile, conditional on real earnings in that year being within the bounds of the centile from step 2. Fifth, for each year, we take the nominal earnings level in each centile and we compute tax liabilities separately by number of children for each state, using the tax and transfer calculator. In the last step, for each education group, year, state and number of children, we compute

\footnote{Gruber and Saez (2002) use this approach to estimate taxable income elasticities; however, we are not aware of any papers that use this approach to estimate extensive margin labor supply responses.}
the weighted-mean of the tax liabilities across centiles using the (time- and state-invariant) education distribution from step 3 as weights. This leaves us with instruments that are cell means, where the cells are defined by education group, year, state, and number of children, with variation driven solely by exogenous changes in the tax code, and not by endogenous changes in the earnings and/or demographics distribution. Finally, for the simulated macro tax liability, we aggregate micro tax liabilities across family types using weights for number of children that vary by education group, but are time- and state-invariant. All tax liabilities are adjusted for inflation using the consumer price index for all urban consumers with 2010 as the base year. The simulated cell average (micro and macro) tax liabilities are then matched back to the CPS data and used as instruments for imputed tax liabilities, among individuals in a given cell, in a two-stage least squares regression.

Panel C of Table 5 shows the mean imputed real earnings for each education group averaged over the years and the corresponding tax and transfer levels depending on the number of children in the household. All numbers are reported in real 2010 U.S. dollars (USD). For high school dropouts, taxes (transfers) are strongly decreasing (increasing) in the number of children. The welfare benefit for households with no children is driven entirely by SNAP since these households are ineligible for AFDC or TANF. For bachelor degree holders, the range is very small and close to 0 since most are ineligible for these mean-tested benefits. Importantly, the reported welfare benefits do not incorporate recipiency rates which are much less than 100 percent during our sample period. The last four rows
report recipiency rates, as estimated in the SIPP. Each individual in the 
CPS is assigned a recipiency rate that we calculate from the SIPP based on 
education, income and year. The table reports the average of the assigned 
recipiency rates separately for AFDC/TANF and food stamps, and also pre- 
and post-1996. We see that for high school dropouts, recipiency rates are 
roughly 50 percent for AFDC/TANF but fall to 20 percent post-1996. For 
food stamps, recipiency rates are much more comparable pre- and post- 
1996 and equal to roughly 40 percent.\textsuperscript{54} These recipiency rates decrease 
with education which reflects diminishing eligibility as earnings increase.

\section{10.2 Empirical Method}

\textbf{Specification of Labor Markets}

In the theoretical model, individuals sort themselves into \( l + 1 \) distinct 
occupations. For our empirical analysis, a key difficulty is ranking indi-
viduals, including the non-employed, according to their potential income if 
they work. For this purpose, we approximate the labor market an individ-
ual may participate in by her educational attainment (high school dropout, 
high school graduate, some college), state and time (year-month). We as-
sume that individuals are perfect substitutes within labor markets and 
use \((e,s,t)\) to denote these cells. This labor market definition is consistent 
with Rothstein (2010).

\textsuperscript{54}For AFDC/TANF, we calculate recipiency rates based on sample of mothers since 
single women with no children are not eligible for these programs.


Estimating Micro and Macro Participation Responses and Macro Employment Responses

Equation (19) shows that the optimal tax schedule can be expressed in terms of macro employment responses and the ratio of macro to micro participation responses in matrix terms. Ideally one would attempt to estimate the matrix of macro participation responses $\frac{\partial \kappa_i}{\partial T_j}$, the matrix of micro participation responses $\frac{\partial \kappa_i}{\partial T_j}$ Micro and the matrix of macro employment responses $\frac{\partial H_i}{\partial T_i}$ for all labor markets $i,j$. However, this would lead to a very large number of cross effects to estimate that would be difficult to identify, especially the macro responses. Thus, for the purpose of estimation, we focus on the no-cross effects case where the above mentioned matrices are diagonal. We also assume away income effects by estimating the responses to employment tax liabilities $T_i + b$, instead of estimating separately the responses to tax liability $T_i$ and to benefit $b$.

In our model $H_i$ and $K_i$ correspond to the number of individuals in income group $i$, but for an empirical specification that uses variation across individuals and labor markets, it makes little sense to assume $\frac{\partial \kappa_i}{\partial T_i}$ or $\frac{\partial H_i}{\partial T_i}$ are constant across labor markets. Instead we will estimate the effect of taxes $T_i$ on employment and participation rates. We denote the employment rate in income group $i$, which in our empirical setting will correspond to an education group $i$, as $\hat{H}_i$ and the participation rate as $\hat{K}_i$. These are the fraction of individuals with education level $i$ who are employed or participating in the labor force, respectively. Estimating the marginal effects of taxes on employment and participation rates furthermore has the important advantage that the estimates are easier to interpret and to compare.
to the prior literature. For example, these estimates are straightforward to convert to employment and participation elasticities.

To obtain an econometric specification for the responses to taxation that is motivated by the theoretical model (without cross effects), we make two assumptions. First, we assume that the conditional employment probability and wage in a market can be written as functions of the average tax liability in that market only.\textsuperscript{55} Second, we assume that tax liabilities vary across individuals within a labor market according to the number \(n\) of children in the household.\textsuperscript{56} The function describing participation decisions for individual \(m\) in labor market \((e,s,t)\) can thus be written as:

\[
\hat{K}_{m,e,s,t,n}(t) = \bar{K}_{m,e,s,t,n}(p_{e,s,t}(T_{e,s,t}), w_{e,s,t}(T_{e,s,t}), s_{e,s,t,n})
\]

(22)

To estimate the micro participation response, we take a linear approximation to Equation (22), add labor market fixed effects (one FE for each state-by-year-by-month-by-education cell) and flexible controls (education by number of children FE, and demographic control variables like age, age-squared, race, ethnicity all interacted with education groups), to get the following econometric specification:

\[
\hat{k}_{m,e,s,t,n} = T_{e,s,t,n} \beta + \delta_{e,s,t} + \delta_{e,n} + X_{m,e,s,t,n} \lambda + \nu_{m,e,s,t,n}
\]

(23)

This equation implies that \(\beta = \frac{\partial \hat{K}_{m,e,s,t,n}}{\partial T_{e,s,t,n}}\) \textsuperscript{Micro} captures the micro participa-

\textsuperscript{55}The restrictions on the econometric specification correspond to the no-cross effect theoretical assumption that is assumed in Proposition 1 and Corollary 1.

\textsuperscript{56}Moffit (1998) argues that the literature features very heterogeneous marriage and fertility responses to taxes and transfers across studies, with a large number of studies finding no effect. As a result, he concludes that much more research remains to be done.
tion effect. Implicit in this specification is a pooling assumption, whereby the partial derivative of taxes on participation does not vary across labor markets. We adopt this assumption for simplicity and because it is difficult to generate exogenous variation in tax liabilities that differentially affects income groups.

Next, to estimate macro participation responses, we aggregate the data to state-year-education averages, add education-by-year and education-by-state fixed effects, region specific linear time trends, and demographic controls (cell averages of the micro controls) interacted with education to get:

$$\hat{k}_{e,s,t} = T_{e,s,t} \gamma + \delta_{e,s} + \delta_{e,t} + X_{e,s,t} \lambda + v_{e,s,t}$$

(24)

The macro effect is defined as the change in individual participation probabilities if the tax liabilities for all individuals in a labor market increase by one dollar. Therefore the macro effect can be obtained as:

$$\frac{\partial \hat{k}_{e,s,t}}{\partial T_{e,s,t}} = \gamma.$$\(^{57}\)

The market-level employment rate in market \((e, s, t)\) is given by

$$\hat{H}_{e,s,t}(T_{e,s,t}) = p_{e,s,t}(T_{e,s,t}) \times \hat{k}_{e,s,t}(T_{e,s,t}).$$

Thus, the macro employment response is given by \(\frac{\partial \hat{H}_{e,s,t}}{\partial T_{e,s,t}} = p_{e,s,t} \times \frac{\partial \hat{k}_{e,s,t}}{\partial T_{e,s,t}} + \hat{k}_{e,s,t} \times \frac{\partial p_{e,s,t}}{\partial T_{e,s,t}}.\) We will rely on a linear approximation for the market-level employment rate similar to Equation (24) and we will estimate the macro employment response in a way that is analogous to how we estimate the macro participation response.

\(^{57}\)Note that without income effects, \(\frac{\partial \hat{k}_{i}}{\partial T_{i}} = \frac{\partial \hat{k}_{i}}{\partial b}.\) In this case, only the difference in taxes and transfers between working and not working matters \(T_i - T_i(0) = T_i + b,\) and therefore \(\frac{\partial \hat{k}_{i}}{\partial T_{i}} = \frac{\partial \hat{k}_{i}}{\partial b} = \frac{\partial \hat{k}_{i}}{\partial (T_i + b)}.\) For our main specification, we will assume no income effects and therefore estimate directly \(\frac{\partial \hat{k}_{i}}{\partial T_{i}}\) thereby using both variation in \(T_i\) and \(b\) to estimate the parameter of interest with maximum power. We tested whether the condition \(\frac{\partial \hat{k}_{i}}{\partial T_{i}} = \frac{\partial \hat{k}_{i}}{\partial b}\) holds and found that the difference was very small and statistically insignificant. We therefore only report results under the no income effect assumption.
Identification

To identify the parameter $\beta$, we require that the micro tax liability $T_{e,s,t,n}$ is exogenous, conditional on labor market and education-by-number of children fixed effects and observables. Similarly, our identifying assumption for $\gamma$ is that the macro tax liability $T_{e,s,t}$ is exogenous, conditional on education-by-state and education-by-year fixed effects and observables. Thus, two independent sources of exogenous variation in tax liabilities are needed. For the micro response $\beta$, we require variation in tax liabilities across individuals within the same labor market. For the macro response $\gamma$, we require variation in average tax liabilities between labor markets.

As described above, our strategy is to generate such variation using a simulated instrument approach. The policy variation in the micro tax liability is illustrated in Figure 8a). This figure plots the average value of the micro simulated tax liability, by year and number of children, relative to the value in 1984, for high school dropouts. One can see that there is substantial variation in taxes over time and this variation is very different across the number of children. Much of this is driven in large part by the EITC. In particular, the TRA86 reform can be clearly seen in 1986-1987, but is quite small relative to the expansions in the 1990s, which also introduced differential EITC levels for parents with one or two children. Finally in 2009, the EITC was expanded for parents with 3 children, as can be seen in the figure, and income taxes were cut for all family types. The identification strategy is similar to the one used by Eissa and Liebman (1996), Meyer and Rosenbaum (2001b) and Gelber and Mitchell (2012).

The policy variation in macro tax liability comes mainly from changes
in state income taxes; in particular, the state-level EITCs and welfare benefits, which vary across states and over time. The large expansions of the federal EITC, that much of the literature has relied on, are not useful, since the change affected all states simultaneously and thus would be collinear with time trends. We illustrate this variation by plotting the macro simulated tax liability for high school dropouts for the largest 12 states in Figure 8b).

A potential concern with our identification strategy is that single women might move to avoid taxes or receive higher benefits. However, several papers (e.g. Meyer, 2000, Kennan and Walker, 2010) suggest that this response is at best modest, particularly for the sample of low income women that are the focus of this study. Thus, while migration responses might be important in other contexts, we do not believe that our estimates will be confounded by them.

10.3 Empirical Results

For all of our empirical results, we report Instrumental Variables (IV) estimates from a Two-Stage Least Squares (2SLS) regression. Reported standard errors in all regressions are clustered on the state level. The notes of the tables contain exact details about the regression specification. All of the OLS results can be found in the online appendix (Section V). Note that in interpreting these results that the tax liabilities are in units of $1000.

The top panel of Table 6 shows the IV estimates for the micro participation (Column 1) and employment (Column 2) responses to taxes and
transfers based on equation (23) above. The results indicate a clear negative and statistically significant participation effect of taxes, consistent with the prior literature. We find that a $1000 increase in taxes leads to a 3.4 percentage point reduction in the participation probability which translates to an elasticity of -0.63. We also see fairly similar micro responses for employment.

Our elasticity estimates are somewhat large but they are within the range of elasticities that is reported in the literature. This is not that surprising since we use similar variation in taxes as the previous literature; in particular, variation driven by the EITC. One notable difference is that past studies typically control for state and year fixed effects, but not their interaction. This yields estimates that confound micro and macro responses (See Rothstein (2010) for a discussion of this). Nevertheless, most of the tax variation in these papers would also have come from across group variation within labor markets.

The macro participation and employment IV estimates are displayed in the second panel of Table 6. These correspond to empirical estimates

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58 Following the theory, we take the marginal effect and multiply it by the ratio of the income gain from employment over the participation rate. For example, if we take the marginal effect of -0.034 and multiply it by the ratio $14.26/0.77, we get an elasticity of -0.63.

59 The online appendix (Section V) reports the OLS regression results. We see that the OLS participation responses are attenuated relative to our IV estimates. For the full sample, the micro participation elasticity is 0.09 and the macro participation elasticity is -0.8. The micro and macro employment responses are of a similar magnitude. This highlights the importance of instrumenting for the micro and macro tax liabilities. In general the OLS results are not very informative, for example there is a strong reverse causality issue where high participation rates will be associated with lower earnings (due to selection) and higher employment taxes. Isolating variation coming from tax policy changes is crucial in order to obtain meaningful results.

60 Eissa, Kleven, and Kreiner (2008) report a range of (-0.35,-1.7) with a central elasticity of -0.7.
from a macro-level (education-state-year cells) 2SLS regression of participation and employment rates on market-level tax liabilities, controlling for education-by-state and education-by-year fixed effects and percent black, percent Hispanic, average age, average age-squared, average number of children and their interactions with education and region-specific time trends. Since the number of observations is much smaller and since there is less variation in tax liabilities across labor markets, the coefficients are estimated less precisely. Nevertheless, there is some suggestive evidence that the macro participation and employment responses are smaller than the micro ones. According to Proposition 3, such a finding is consistent with a matching model where the bargaining power is lower than the one prescribed by the Hosios condition.

Our results on micro and macro responses to taxation are generally consistent with the meta analysis conducted in Chetty, Guren, Manoli, and Weber (2012) who report slightly larger estimates of the extensive steady-state elasticities based on micro evidence than macro evidence. It is worth noting that the macro-based studies cited in Chetty, Guren, Manoli, and Weber (2012) are based on cross-country evidence that typically comes from a limited number of OECD countries. Nevertheless, it is reassuring to note that our results are similar, based on a panel data approach across all states, over time, in the U.S.

A concern with our macro estimates, which are identified by state-year variation in tax liabilities, is that they may be confounded by policy endogeneity. In particular, states may endogenously set taxes and welfare benefits based on prevailing local economic conditions. Our baseline es-
timates control for region-specific time trends which should partially address this issue. To further explore the robustness of our estimates, we consider several alternative specifications and report the results in Table 3. Table 7 provides a series of robustness tests. The first column reports our baseline estimates for comparison. In columns 2-4 we drop the region-specific time trends from the regressions and include alternative controls for pre-trends. Since the micro participation regressions control for year by state fixed effects, these are not affected (Panel A), but Panel B and C show that the macro responses are very robust to controlling for division-by-year fixed effects, region-by-year fixed effects and no controls for pre-trends. In column 5 we present our results dropping state taxes (state EITC and state income taxes) from our imputed tax liability and instrument, as those may be endogenous, as Hoynes and Patel (2015) have argued. While this slightly reduces the precision of our macro estimates, the results are qualitatively similar. Finally, Column 6 controls for the state unemployment rate interacted with education as a proxy for the state specific economic environment and shows a very similar pattern. Overall, the robustness of our estimates suggest that policy endogeneity is not of first-order importance in our setting.\textsuperscript{61}

Finally, Table 8 considers behavioral responses over the business cycle. In particular, this allows us to test whether spillovers are larger in recessions, as some recent research has found. We rely on several proxies

\textsuperscript{61}In column 7 we show our results when we calculate tax liabilities assuming that all individuals who would be eligible to receive AFDC, TANF or food stamps based on their income actually take-up benefits. Since this leads to larger calculated tax liabilities (and values for the instruments), the estimated marginal effects and elasticities are reduced, but the result that macro participation responses are larger than micro participation responses is actually more pronounced.
for the business cycle: the 6-month change in the unemployment rate, the state unemployment rate and an indicator for whether the unemployment rate exceeds 9 percent. Across all specifications, we see that micro and macro participation and employment responses tend to be lower when the unemployment rate is relatively high. This is consistent with results in Schmieder, Von Wachter, and Bender (2012) and Kroft and Notowidigdo (2014). There is also some suggestive evidence that the micro-macro participation gap increases in weak labor markets; for instance, for the 6-month change in unemployment specification, the gap is roughly 0.1 in weak labor markets but only 0.01 in strong labor markets. We emphasize however, that lack of precision limits any strong conclusion about how the gap varies over the cycle.

Overall, these results suggest that while micro labor supply responses are sizeable and in line with what the literature has found before, they may not always be good approximations for the macro employment responses. In particular our evidence broadly suggests that macro responses tend to be lower than micro responses. Although this is some of the first evidence on the gap between micro and macro elasticities, it is however worth noting that our macro estimates are less precisely estimated than our micro ones. Such discrepancy can easily been explained by the limited policy variations at the state level over time, compared to policy variations across women with different number of kids over time. Future research should use other source of policy variations as robustness checks for our macro estimates.
11 Simulating the Optimal Tax Schedule

In this section we show how unemployment and wage responses affect the shape of the optimal tax and transfer schedule. For this purpose we simulate the optimal tax schedule using the sufficient statistics formula for the optimal tax and transfer schedule. In line with the empirical section, we focus on the no-cross effects model with its restricted set of sufficient statistics. These simulations are very stylized and should be viewed as an illustration of the comparative statics of our optimal tax formula, that highlight the importance of taking spillovers into account. The resulting tax schedule should not be viewed as a precise attempt to derive the optimal tax schedule for any particular population.\(^{62}\)

To simulate the optimal tax schedule, we solve the system of first-order conditions derived in the theoretical section for the tax levels at different income levels. The system contains \(N + 2\) unknowns, the \(i = 0\ldots N\) tax levels \(T_i\) as well as the lagrange multiplier \(\lambda\), and \(N + 2\) equations, the first-order conditions (17) and (15) and the government budget constraint (6). Since we focus on the no-cross effects model, the first-order conditions for the tax levels simplify to Equation (17).\(^{63}\) We partition the income distribution into discrete bins, corresponding to the zero income level, the 3

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\(^{62}\) Such an exercise for the U.S. would, for example, have to take into account that policy makers seem to have placed different welfare weights on different groups of single women, depending on the number of children. Backing out the implicit welfare weights in the current tax schedule given an optimal tax framework and calibrating how the tax schedule given these welfare weights would change under alternative models would be very interesting, but beyond the scope of this paper.

\(^{63}\) In order to express the FOC for the benefit level in terms of sufficient statistics, we make two assumptions: a) benefits do not affect wages or job finding probabilities in any labor market and b) the social welfare function is linear in expected utilities (Benthamite Utilitarian). This can be viewed as an approximation that in practice likely does not make a big difference for the results.
education groups in our empirical analysis, as well as a 4th group: single
women with Bachelor degrees, which we did not use in our empirical anal-
ysis due to the lack of identifying policy variation for this group. We take
the average number of individuals over all years as the population shares
of the education groups and assign to each group the average income over
our sample period. In order to solve the system of equations we also have
to parameterize $g_i(T_i)$ and $h_i(T_i)$. Following Saez (2002) we parameterize $g_i$
using the functional form: $g_i = \frac{1}{\lambda(w^0_i - T^0_i)^\nu}$, where $\nu$ is the parameter describ-
ing society’s parameter for redistribution. We set $\nu = 0.5$, which leads to
optimal tax schedule similar to the observed schedules, but in the online
appendix (Section V) we also report results for $\nu = 1$. We use a first order
Taylor approximation to describe $h_i$, which should provide a reasonable
approximation as long as the optimum is close to the current policy:

$$h_i = h_i^0 + \frac{\partial H_i}{\partial (T_i + b)} \left( (T_i + b) - (T_i^0 + b^0) \right). \tag{25}$$

We present simulations of the optimal tax schedule based on the for-
mula derived in this paper, which we refer to as the KKLS formula, and
contrast this tax schedule with simulations based on the optimal tax for-
mula in Saez (2002).

Figure 14a) shows the optimal tax and transfer schedule for the low-
est 3 education groups using the employment and participation response estimates from our empirical section. The dashed line with circles shows
the optimal tax schedule implied by our no-cross effects welfare formula,
which relies on the micro-macro participation gap to correct for spillovers.
The figure also shows the corresponding optimal tax schedule implied by the pure extensive margin optimal tax formula in Saez (2002). The Saez (2002) formula relies only on employment responses but does not specify whether these are micro or macro responses. For the solid line with stars we implement the Saez (2002) formula using our micro employment response estimates, while for the red line we use the macro estimates. Compared to using the Saez (2002) formula with macro employment responses, our formula implies a lump sum transfer to the non-employed about twice as big and higher marginal tax rates (a flatter slope). This is because our estimates imply lower macro than micro participation responses, so that the spillover effects attenuate the welfare gain of a transfer to the working poor. The Saez (2002) formula calibrated with macro employment responses implies larger transfers at the bottom than when micro employment responses are used for calibration and a somewhat flatter slope. This is because we estimate larger micro employment responses than macro ones. To highlight the differences in the slopes, Figure 14b) shows the implied employment tax rates, i.e. \( \frac{T_i + b \omega_i}{\omega_i} \), at each income level. Clearly the Saez (2002) formula with micro employment effects generates the lowest employment tax rate, which is in fact negative like the EITC. Saez (2002) with macro employment effects, generates larger employment tax rates that is only slightly negative and finally the KKLS optimal tax formula yields an employment tax rate that for the lowest income group is positive, thus resembling more an NIT.

In Figure 15a) we show how, holding the macro employment response constant, the macro-micro participation ratio affects the optimal tax sched-
The line with circles shows the benchmark tax schedule from Figure 14 using our optimal tax formula with our main empirical estimates. The line with stars shows the optimal tax schedule using our formula when we double the macro-micro participation ratio but everything else constant. This captures a situation where the spillovers from an increase in employment taxes are positive (more labor market participants make it easier for people to find jobs). This makes the tax profile steeper and the optimal tax is a clearly EITC-like schedule, as Figure 15b) shows the employment tax rate is indeed negative at the bottom. The line with plus signs on the other hand shows the optimal tax schedule when we cut the macro-micro participation ratio to 0.5, thus leading to large negative spillovers where the macro response is smaller than the micro response. This makes the overall tax profile much flatter and the benefits to the non-employed larger, mirroring an NIT situation.

Other papers have stressed the possibility that macro employment responses could be significantly lower than micro employment responses, particularly in the context of UI and job search assistance and this has typically been explained by the possibility of job rationing at least in the short run, especially during recessions. Our estimates in Table 8, while noisy, are consistent with this view: while both macro and micro responses decline in recessions, the decline is much larger for macro responses, both with respect to employment and participation. The business cycle macro estimates suggest that spillover effects could be larger during economic downturns. Figure 16 simulates how the optimal tax schedule would vary over the business cycle given our estimates from Table 8. We present
results from the estimates based on the 6 month change in the unemployment rate here, but using the other measures yields qualitatively very similar results. In Figure 16a) and 16b) we show the optimal tax schedule for different business cycle states implied by our (KKLS) optimal tax formula. The transfer at zero income is around 4000 USD during a strong labor market with a negative employment tax of about -10 percent for moving from zero income to the first income group. During weak labor markets the simulation suggests that the transfer at zero should increase to 7000 USD per year with a much higher employment tax of about 23 percent. In contrast, panels (c) and (d) of Figure 16 show the tax schedule implied by the Saez (2002) formula using the macro employment effects estimated over the business cycle.

While the decline in macro employment responses during weak labor markets also leads to an increase in transfers at the bottom and a slight increase in employment tax rates, the change is comparatively modest due to the absence of the spillover channel.

12 Conclusion

This paper revisits the debate about the desirability of the EITC versus the NIT. We have shown that whether the optimal employment tax on the working poor is positive or negative depends on the presence of unemployment and wage responses to taxation. Our sufficient statistics optimal tax formula, combined with our reduced-form empirical estimates, indicate that the optimal policy is pushed more towards an NIT than the

\footnote{Using the micro employment effects yields even less variation in the optimal tax schedule over the cycle.}
standard optimal tax model would suggest, although statistical precision limits strong conclusions about the magnitude of the macro responses.

There are several limitations to our analysis that should be addressed in future work. First, there is clearly a need for better empirical estimates of the macro effects of taxation. Most studies of macro labor supply responses rely on cross-country variation in taxes, which can be substantial. While this variation is clearly desirable for efficiency reasons, across countries, tastes for redistribution and other forms of government spending are probably correlated with taxes and employment and are difficult to fully control for. What is needed is reliable policy variation in taxes across labor markets, similar to variation in UI benefit payments that is exploited in Lalime, Landais, and Zweimüller (2015). Second, it would be very interesting to study business cycle effects of taxation more directly by introducing dynamics into the model. The approach we adopted in this paper is entirely steady-state. Finally, it would be useful to develop a model that more fully integrates UI benefits and income taxes, where benefits depend on prior wages, as is currently the policy in most developed economies.
Table 5: Variable Means for Single Women

<table>
<thead>
<tr>
<th>Panel A: Demographics</th>
<th>(1) Full Sample</th>
<th>(2) High School Dropout</th>
<th>(3) High School Graduate</th>
<th>(4) Some College</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>34.1</td>
<td>33.6</td>
<td>33.9</td>
<td>34.5</td>
</tr>
<tr>
<td>No Children Percent</td>
<td>65.1</td>
<td>59.6</td>
<td>65.8</td>
<td>67.0</td>
</tr>
<tr>
<td>1 Child Percent</td>
<td>17.7</td>
<td>16.9</td>
<td>17.8</td>
<td>18.0</td>
</tr>
<tr>
<td>2 Children Percent</td>
<td>10.8</td>
<td>12.3</td>
<td>10.6</td>
<td>10.3</td>
</tr>
<tr>
<td>3+ Children Percent</td>
<td>6.3</td>
<td>11.2</td>
<td>5.8</td>
<td>4.7</td>
</tr>
<tr>
<td>Mean Years of Education</td>
<td>12.0</td>
<td>9.3</td>
<td>12</td>
<td>13.3</td>
</tr>
<tr>
<td>Percent Black</td>
<td>21.0</td>
<td>24.7</td>
<td>21.5</td>
<td>18.7</td>
</tr>
<tr>
<td>Percent Hispanic</td>
<td>14.6</td>
<td>30.0</td>
<td>12.2</td>
<td>10.0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Labor Force Status</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor Force Participation Rate ( (k_i) )</td>
<td>76.9</td>
<td>55.2</td>
<td>78.3</td>
<td>85.3</td>
</tr>
<tr>
<td>Employment Rate ( (h_i) )</td>
<td>70.2</td>
<td>45.9</td>
<td>71.4</td>
<td>80.2</td>
</tr>
<tr>
<td>Unemployment Rate ( (1 - p_i) )</td>
<td>9.3</td>
<td>17.1</td>
<td>8.9</td>
<td>6.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Income, Taxes and Transfers (Real 2010 Dollars)</th>
<th>(1) Full Sample</th>
<th>(2) High School Dropout</th>
<th>(3) High School Graduate</th>
<th>(4) Some College</th>
</tr>
</thead>
<tbody>
<tr>
<td>Imputed Pre-tax Wage Earnings</td>
<td>17463</td>
<td>10021</td>
<td>16925</td>
<td>21503</td>
</tr>
<tr>
<td>Net Taxes: No Children</td>
<td>3929</td>
<td>1667</td>
<td>3717</td>
<td>5092</td>
</tr>
<tr>
<td>AFDC/TANF and Food Stamps: No Children</td>
<td>644</td>
<td>1355</td>
<td>638</td>
<td>359</td>
</tr>
<tr>
<td>AFDC/TANF and Food Stamps: 2 Children</td>
<td>3748</td>
<td>7177</td>
<td>3666</td>
<td>1944</td>
</tr>
<tr>
<td>Net Tax and Transfers ( (T_i) ): No Children</td>
<td>3285</td>
<td>312</td>
<td>3079</td>
<td>4733</td>
</tr>
<tr>
<td>Net Tax and Transfers ( (T_i) ): 2 Children</td>
<td>-4564</td>
<td>-9168</td>
<td>-4951</td>
<td>-1569</td>
</tr>
<tr>
<td>Net Tax and Transfers ( (b) ): Zero Income. No Children</td>
<td>-2070</td>
<td>-2055</td>
<td>-2069</td>
<td>-2077</td>
</tr>
<tr>
<td>Net Tax and Transfers ( (b) ): Zero Income. 2 Children</td>
<td>-11477</td>
<td>-11546</td>
<td>-11442</td>
<td>-11480</td>
</tr>
<tr>
<td>AFDC/TANF Recipiency Rate for Mothers: Pre-1996</td>
<td>29</td>
<td>49</td>
<td>25</td>
<td>17</td>
</tr>
<tr>
<td>AFDC/TANF Recipiency Rate for Mothers: Post-1996</td>
<td>11</td>
<td>21</td>
<td>10</td>
<td>6</td>
</tr>
<tr>
<td>Food Stamp Recipiency Rate: Pre-1996</td>
<td>21</td>
<td>41</td>
<td>19</td>
<td>10</td>
</tr>
<tr>
<td>Food Stamp Recipiency Rate: Post-1996</td>
<td>22</td>
<td>41</td>
<td>23</td>
<td>15</td>
</tr>
</tbody>
</table>

Number of observations: 773367, 138766, 334359, 300242

Notes: The sample is restricted to single women aged 18-55. All dollar figures are in real 2010 dollars. Data used in each column are restricted to women with the education level in the column header. Imputed earnings result from a linear regression of demographics on wages conditional on employment. Net Taxes is federal, state and fica (sum of employer and employee) tax liabilities net of tax credits, including EITC. AFDC/TANF and Food Stamps assume 100 percent recipiency among those eligible based on income. Net Taxes and Transfers is the net of federal, state and fica (sum of employer and employee) tax liabilities and credits, AFDC or TANF payments and food stamp benefits.
Table 6: Micro and Macro Responses to Changes in Taxes and Benefits

<table>
<thead>
<tr>
<th>LHS Variable</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participation Rate: $\hat{K}_i$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment Rate: $\hat{H}_i$</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Micro Response</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Taxes Plus Benefits</td>
<td>-0.034</td>
<td>-0.033</td>
</tr>
<tr>
<td></td>
<td>[0.002]**</td>
<td>[0.002]**</td>
</tr>
<tr>
<td>Num. Obs</td>
<td>773367</td>
<td>773367</td>
</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>0.77</td>
<td>0.70</td>
</tr>
<tr>
<td>Inc Gain from Employment (2010USD)</td>
<td>14259.0</td>
<td>14259.0</td>
</tr>
<tr>
<td>Tax Elasticity</td>
<td>-0.63</td>
<td>-0.66</td>
</tr>
<tr>
<td><strong>Macro Response</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg Taxes Plus Benefits within Labor Market</td>
<td>-0.030</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>[0.017]*</td>
<td>[0.018]</td>
</tr>
<tr>
<td>Num. Obs</td>
<td>4284</td>
<td>4284</td>
</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>0.74</td>
<td>0.67</td>
</tr>
<tr>
<td>Inc Gain from Employment (2010USD)</td>
<td>12479.3</td>
<td>12479.3</td>
</tr>
<tr>
<td>Tax Elasticity</td>
<td>-0.51</td>
<td>-0.51</td>
</tr>
</tbody>
</table>

**Notes:** (* P<.1, ** P<.05, *** P<.01) Standard errors clustered on state level. The sample is restricted to single women aged 18-55. The data include March CPS for 1984-2011 and Outgoing Rotations Groups for 1994-2010. The first column uses labor force participation as the outcome variable, the second column uses employment status. Taxes Plus Benefit is the net of federal (including EITC), state and fica (sum of employer and employee) taxes plus the benefits an individual would be eligible for at no earnings, adjusted for national recipiency rates. The Micro Response regressions use individual level data and include controls for age, age-squared, race, ethnicity and fixed effects for number of children and State x Year x Month fixed effects, all interacted with education. The Macro Response regressions use data that are collapsed to the state-year cell, each cell receives equal weight in the regression. Regressions include controls (all interacted with education) for percent black, percent hispanic, average age, age-squared, number of children and fixed effects for state and year and CPS region time trends.
Table 7: Alternative Estimates of Participation and Employment Responses

<table>
<thead>
<tr>
<th>(1) Region Time Trend</th>
<th>(2) Div X Year FE</th>
<th>(3) Reg X Year FE</th>
<th>(4) No Pre-Trends</th>
<th>(5) No State Taxes</th>
<th>(6) State-Unemp.</th>
<th>(7) Full Take-up</th>
</tr>
</thead>
</table>

**Micro Participation Response**

<table>
<thead>
<tr>
<th>Taxes Plus Benefits</th>
<th>-0.034</th>
<th>-0.034</th>
<th>-0.034</th>
<th>-0.034</th>
<th>-0.038</th>
<th>-0.034</th>
<th>-0.019</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>[0.002]**</td>
<td>[0.002]**</td>
<td>[0.002]**</td>
<td>[0.002]**</td>
<td>[0.002]**</td>
<td>[0.002]**</td>
<td>[0.001]**</td>
</tr>
<tr>
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<td>773367</td>
<td>773367</td>
<td>773367</td>
<td>773367</td>
</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>0.77</td>
<td>0.77</td>
<td>0.77</td>
<td>0.77</td>
<td>0.77</td>
<td>0.77</td>
<td>0.77</td>
</tr>
<tr>
<td>Income Gain from Employment</td>
<td>14259</td>
<td>14259</td>
<td>14259</td>
<td>14259</td>
<td>14501</td>
<td>14259</td>
<td>15475</td>
</tr>
<tr>
<td>Tax Elasticity</td>
<td>-0.63</td>
<td>-0.63</td>
<td>-0.63</td>
<td>-0.63</td>
<td>-0.72</td>
<td>-0.63</td>
<td>-0.38</td>
</tr>
</tbody>
</table>

**Macro Participation Response**

<table>
<thead>
<tr>
<th>Avg Taxes Plus Benefits</th>
<th>-0.030</th>
<th>-0.035</th>
<th>-0.034</th>
<th>-0.039</th>
<th>-0.031</th>
<th>-0.031</th>
<th>-0.008</th>
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</thead>
<tbody>
<tr>
<td>within Labor Market</td>
<td>[0.017]*</td>
<td>[0.025]</td>
<td>[0.020]*</td>
<td>[0.017]**</td>
<td>[0.024]</td>
<td>[0.017]**</td>
<td>[0.007]</td>
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<tr>
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<td>4284</td>
<td>4284</td>
<td>4284</td>
<td>4284</td>
<td>4284</td>
<td>4284</td>
</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>0.74</td>
<td>0.74</td>
<td>0.74</td>
<td>0.74</td>
<td>0.74</td>
<td>0.74</td>
<td>0.74</td>
</tr>
<tr>
<td>Income Gain from Employment</td>
<td>12479</td>
<td>12479</td>
<td>12479</td>
<td>12479</td>
<td>12695</td>
<td>12479</td>
<td>13914</td>
</tr>
<tr>
<td>Tax Elasticity</td>
<td>-0.51</td>
<td>-0.58</td>
<td>-0.56</td>
<td>-0.65</td>
<td>-0.53</td>
<td>-0.53</td>
<td>-0.14</td>
</tr>
</tbody>
</table>

**Macro Employment Response**

<table>
<thead>
<tr>
<th>Avg Taxes Plus Benefits</th>
<th>-0.027</th>
<th>-0.031</th>
<th>-0.026</th>
<th>-0.034</th>
<th>-0.038</th>
<th>-0.031</th>
<th>-0.010</th>
</tr>
</thead>
<tbody>
<tr>
<td>within Labor Market</td>
<td>[0.018]</td>
<td>[0.026]</td>
<td>[0.022]</td>
<td>[0.019]*</td>
<td>[0.026]</td>
<td>[0.017]**</td>
<td>[0.009]</td>
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<tr>
<td>Num. Obs</td>
<td>4284</td>
<td>4284</td>
<td>4284</td>
<td>4284</td>
<td>4284</td>
<td>4284</td>
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</tr>
<tr>
<td>Mean of Dep. Var.</td>
<td>0.67</td>
<td>0.67</td>
<td>0.67</td>
<td>0.67</td>
<td>0.67</td>
<td>0.67</td>
<td>0.67</td>
</tr>
<tr>
<td>Income Gain from Employment</td>
<td>12479</td>
<td>12479</td>
<td>12479</td>
<td>12479</td>
<td>12695</td>
<td>12479</td>
<td>13914</td>
</tr>
<tr>
<td>Tax Elasticity</td>
<td>-0.51</td>
<td>-0.58</td>
<td>-0.49</td>
<td>-0.64</td>
<td>-0.72</td>
<td>-0.57</td>
<td>-0.20</td>
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</tbody>
</table>

**Notes:** (* P < .1, ** P < .05, *** P < .01) Standard errors clustered on state level. The sample is restricted to single women aged 18-55. The data includes March CPS for 1984-2011 and Outgoing Rotations Groups for 1994-2010. Our baseline specification from Table 3 is contained in column (1). Column (2) replaces region-specific linear time trends with division-by-year fixed effects. Column (3) replaces region-specific linear time trends with region-by-year fixed effects. Column (4) drops region-specific linear time trends. Column (5) is our baseline specification but drops state taxes, including state EITC supplements, from both the OLS and IV tax liabilities. Taxes Plus Benefit is the net of federal (including EITC), state and fica (sum of employer and employee) taxes plus the benefits an individual would be eligible for at no earnings, adjusted for national recipiency rates. Column (6) controls for the state unemployment rate interacted with education. Column (7) is our baseline specification but assumes 100 percent take-up rates for AFDC/TANF and Food Stamps for the computation of the imputed tax liability and the simulated instrument.
Table 8: Participation and Employment Responses: Heterogeneous Labor Market Conditions

<table>
<thead>
<tr>
<th></th>
<th>(1) Regression Coef.</th>
<th>(2) Extrapolated Marg. Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panels A: Micro Participation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6-mo change in unemp</td>
<td>-0.034 0.002***</td>
<td>0.011 0.0004***</td>
</tr>
<tr>
<td>State unemp. rate</td>
<td>-0.035 0.002***</td>
<td>0.012 0.0003***</td>
</tr>
<tr>
<td>Unemp above 9 pct</td>
<td>-0.035 0.002***</td>
<td>0.053 0.0013***</td>
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<tr>
<td><strong>Panels B: Macro Participation</strong></td>
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</tr>
<tr>
<td>6-mo change in unemp</td>
<td>-0.029 0.017*</td>
<td>0.043 0.0030</td>
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<tr>
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<td>-0.034 0.018*</td>
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<td>Unemp above 9 pct</td>
<td>-0.031 0.017*</td>
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<td>State unemp. rate</td>
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<td>Unemp above 9 pct</td>
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<td><strong>Panels D: Macro Employment</strong></td>
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<tr>
<td>Unemp above 9 pct</td>
<td>-0.029 0.017*</td>
<td>0.112 0.0060*</td>
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</table>

Notes: [* P<.1, ** P<.05, *** P<.01] Standard errors clustered on state level. The Micro Response regressions use individual level data and include controls for age, age-squared, race, ethnicity and fixed effects for number of children and State x Year x Month. The Macro Response regressions use data that are collapsed to the state-year cell observations, each cell receives equal weight in the regression. Regressions include controls for percent black, percent hispanic, average age, age-squared, number of children and fixed effects for state and year and CPS Region time trends. Weak and strong labor markets marginal effects assume the market indicator is two standard deviations above or below the mean for the continuous variables.
Figure 8: The Variation in Taxes plus Benefits

(a) Micro Variation in Taxes plus Benefits

(b) Macro Variation in Taxes plus Benefits

Notes: The top figure shows the variation in taxes plus benefits for high school dropouts by number of children normalized such that 1984 equals one. Taxes plus benefits is the net of federal (including EITC), state and fica (sum of employer and employee) taxes plus the benefits an individual would be eligible for at no earnings, adjusted for national recipiency rates. The bottom figure shows residuals from a regression of year fixed effects on the state level average taxes plus benefits with state means added back to the residual, then normalized such that 1984 equals one. Taxes plus benefits is the net of federal (including EITC), state and fica (sum of employer and employee) taxes plus the benefits an individual would be eligible for at no earnings, adjusted for national recipiency rates.
Figure 9: Optimal Tax and Transfer Schedule Comparing KKLS Formula with Saez (2002) Formula

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

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

Notes: Simulations of the optimal tax and transfer schedule under alternate assumptions on employment and participation responses. The optimal schedule is simulated for 5 income groups, corresponding to the 4 education groups in the empirical section and zero income. Distribution of the income groups is calibrated using CPS data. We show the optimal schedule for the lowest 4 groups where the variation of interest lies. The figure uses the participation and employment responses estimated in the paper. The line with circles uses the optimal welfare formula derived in this paper. The dashed line with plus signs uses the Saez (2002) formula based on the estimated macro responses in this paper, while the solid line uses the estimated micro employment responses in this paper.
Figure 10: The Effect of Changing the Macro Participation Effect on the Optimal Tax and Transfer Schedule

(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: Simulations of the optimal tax and transfer schedule under alternate assumptions on employment and participation responses. The optimal schedule is simulated for 5 income groups, corresponding to the 4 education groups in the empirical section and zero income. Distribution of the income groups is calibrated using CPS data. We show the optimal schedule for the lowest 4 groups where the variation of interest lies. The top figure shows the post vs. pre-tax income relationship while the bottom figure shows the employment tax rates. The line with circles shows the optimal tax schedule given the empirical estimates and the KKLS formula. The solid line shows the optimal schedule if the macro responses are multiplied by 0.5 and the line with plus signs if they are multiplied by 2.
Figure 11: Optimal Tax and Transfer Schedule in Weak vs. Strong Labor Markets

Notes: Simulations of the optimal tax and transfer schedule under alternate macro participation responses. The optimal schedule is simulated for 5 income groups, corresponding to the 4 education groups in the empirical section and zero income. Distribution of the income groups is calibrated using CPS data. We show the optimal schedule for the lowest 4 groups where the variation of interest lies. 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 line with circles corresponds to the benchmark simulation using the estimated, participation and employment responses. The solid 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 line with plus signs shows the tax schedule for the corresponding strong labor market estimates from Table 4.
Part III

Labor Market Outcomes of Veterans with Post-2001 Service Time

13 Introduction

The United States military is comprised of over 2 million individuals as of 2013, including active and reserve components. Next to the public education system, the impact of military training on the economy’s aggregate human capital may be larger than any other institution. There are many reasons military service might affect future, post military, labor market outcomes. The military offers intensive training across many disciplines that individuals may be able to leverage in the private labor market after separation. Indeed, Mangum and Ball (1987) show that the likelihood of transferring military training is to civilian employment is similar to the likelihood of transferring training from vocational or technical colleges.

Less tangibly, leadership, self confidence and discipline developed in the military may also increase an individual’s productive capacity in the civilian labor market. Even when a service member finds employment in the same occupation as they would have without military training, these soft skills may increase the individual’s productivity or allow them to get earlier promotions, resulting in higher potential wages. Federal legislation has also affected veterans employment capabilities through programs including “Feds Hire Vets”, helping men and women with past military service find employment in the federal government and “Troops to Teachers”, a program that helps place eligible veterans in public schools as

65See www.fedshirevets.gov for more details.
teachers. On the other hand, service members often enter the military shortly after high school, sacrificing or delaying post-secondary education. By delaying post-secondary education, learning skills may deteriorate, resulting in fewer years of enrollment, or less effective learning upon return from service.

The nature of military service changed dramatically in response to the attack on the World Trade Towers and the Pentagon on September 11, 2001. The United States responded with wars in Afghanistan and Iraq, leading to the longest and most dangerous deployments seen by service members since the Vietnam war. During these deployments, soldiers implemented their training in ways prior service members rarely did on the battlefield. It is plausible that this type of experience might lead to higher returns in the civilian labor market when compared to deployments during a time of relative peace – pre-2001. However, being a soldier post-2001 carried a much higher risk of combat exposure. Soldiers with combat exposure are diagnosed with post-traumatic stress disorder (PTSD), a condition linked to lower employment rates and lower wages (Savoca and Rosenheck, 2000), much more often than counterparts deployed to non-combat zones (Cesur, Sabia, and Tekin, 2013).

In this paper, I analyze the effect of military service on subsequent labor market outcomes for veterans with post-2001 service time compared to labor market outcomes of veterans whose service is limited to the pre-2001 era. While a sizable literature quantifying the effect of military service on job market outcomes already exists, the main contribution of this paper is

\[66^{See troopstoteachers.net for more information.}\]
to describe how the effect differs across types of military experience.

The literature on labor market outcomes of veterans studied soldiers at least as far back as World War II. Cross-sectional comparisons between World War II veterans and non-veterans of the same age revealed that veterans earned more on average and exhibited lower rates of unemployment. Even when controlling for differences in observable demographics, the lifetime earnings of World War II veterans were around 10 percent higher than similar non-veterans (Rosen and Taubman, 1982). The authors note that this result might be anticipated by the armed service selection criteria: while the majority of men from eligible cohorts served in the military during World War II, those who did not were often unfit for service, physically or otherwise. Controlling for positive selection, World War II veterans earned no more than similar non-veterans, perhaps even earning less (Angrist and Krueger, 1994). However, those who reported using their vocational military training in their civilian careers enjoyed long-term earnings premiums. Veterans who did not use their training in their civilian careers did not exhibit earnings premia, suggesting that the benefits of military vocational training may be job-specific (Fredland and Little, 1980).

In contrast to World War II veterans, earnings comparisons suggest Vietnam veterans, on average, earn less than non-veterans (Berger and Hirsch, 1983). While military conscription via the draft was determined, in part, by random assignment, minorities and individuals from lower socioeconomic backgrounds who had fewer resources to avoid the draft were over-represented in the pool of veterans (Cooper, 1977). This leads to the opposite selection problem that researchers face when analyzing World
War II veterans. In a seminal paper, Angrist (1990) uses the draft as a source of randomly assigned risk of Vietnam service in an instrumental variables framework and finds that the effect of Vietnam-era service is a 15 percent earnings reduction measured in the early 1980s, many years after the military experience.

Many of these veterans were subject to extreme stress for prolonged periods of time. According to the National Survey of the Vietnam Generation (NSVG), over 20 percent of Vietnam era veterans suffer from PTSD. PTSD is often coincident with other mental health problems including substance abuse and sleep disorders. A combination of mental disorders may inhibit an individual from assimilating back into society, make it harder to find work, or reduce productivity in the workforce. Savoca and Rosenheck (2000) use the NSGV to study the effect of psychiatric disorders of Vietnam-era veterans on their labor market experiences. They find that PTSD significantly lowers the likelihood of working and the hourly wages of those working. Specifically, a veteran diagnosed with lifetime PTSD was 8.5 percentage points less likely to be working than a veteran without PTSD. Among those working, veterans with PTSD earned an hourly wage $3.60 (in 1999 dollars) less than a veteran without PTSD.

The post-Vietnam military experience is distinct from the World War II and Vietnam era in a number of important ways. First, since the end of the draft in 1973, the United States military has filled its ranks with an entirely volunteer force. Results from the above body of literature may not generalize to those who volunteer for military training. Second, the

67For more on PTSD see www.ptsd.va.gov
Vietnam conflict was followed by an extended period of relative peace. Far fewer military personnel were subject to long tours of duty in hostile environments. To the extent that the earnings and employment penalties suffered by Vietnam veterans can be explained by mental health issues deriving from long combat tours (Savoca and Rosenheck, 2000), the effect of peacetime military service will be different from wartime military service.

Soldiers serving during the 1980s received higher earnings than comparable civilians during their service time and were employed at higher rates post-service. Long-run civilian earnings for service members of this time period are only modestly greater than those without service time and actually lower for white service members (Angrist, 1998), in part because returns from a year of military experience in terms of future earnings are about half of the returns from a year in the civilian labor force (Crane and Wise, 1987).

A third way in which the military has changed since Vietnam is the dramatic increase in the number of women in the military, from around 50,000 in 1973 to nearly 250,000 by 1988. This inspired a strand of literature studying the effects of military service on women. Conclusions are not altogether different from the findings on male veterans: positive returns to military participation, but negative returns to additional years in the military, consistent with a screening explanation (Stranahan, 1998), and a wage disadvantage for white, but not for non-white female veterans (Mehay and Hirsch, 1996).

Lastly, the nature of military experience again changed significantly after the events of September 11, 2001. Since the end of the conflict in
Vietnam and up to the beginning of the wars in Afghanistan and Iraq, the United States military conducted smaller scale—or in the case of Operation Desert Storm in 1991—much shorter military exercises. Peace-time training is a very different experience compared to service time post-September 11. Specifically, the likelihood of a war-zone deployment increased dramatically post-2001. War experience significantly increases the probability of mental health disorders (Hoge, Auchterlonie, and Milliken, 2006, Cesur, Sabia, and Tekin, 2013) in addition to, for obvious reasons, increases in physical disability. Since individuals with mental health disorders such as PTSD suffer earnings penalties (Savoca and Rosenheck, 2000), some of the benefits from military training may be offset by combat induced mental health disorders.

In general, the literature suggests recent veterans enjoy higher earnings (Humensky, Jordan, Stroupe, and Hynes, 2013, Kleykamp, 2013) and tend to be employed at a lower rate (Faberman and Foster, 2013, Humensky, Jordan, Stroupe, and Hynes, 2013, Kleykamp, 2013). However the effects are heterogenous: female veterans tend to enjoy a premium while males suffer a penalty (Gottschalck and Holder, 2009). Even within the subsample of female veterans, the earnings premium is concentrated among older female veterans, while younger female veterans may actually suffer an earnings penalty (Prokos and Padavic, 2000).

The rest of the paper is organized as follows: Section 14 briefly introduces relevant information regarding military contracts, Section 15 describes the data used for empirical analysis, Section 16 lays out the empirical strategy and discusses the results, Section 17 concludes.
14 Military Contracts

The nature of military contracts has important implications for the empirical analysis. This section briefly describes the aspects of military contracts relevant to this paper.

The most basic eligibility requirement is that an entrant must 18 years or older (or 17 with parental consent). The applicant must also pass an aptitude test and a physical.

Once an individual enlists, military service can be broken up into three categories: active duty, active reserve, and inactive ready reserve. Active duty is a full time job and these service members, by and large, do not participate in the civilian labor market. Active reserve members train with their unit on a regular basis, typically one weekend a month and two weeks in the summer. These service members are usually able to participate in the civilian labor force concurrent with their active reserve service time (though many are full time students). Inactive ready reserve members do not typically train on a regular basis. In general, a service member of any type is eligible to be activated for a deployment. Active reservists and inactive ready reservists become active duty service members in the event of a deployment and return to their prior status upon completion of the deployment.

Regardless of the branch of service, all initial contracts are for a period of eight years. During those eight years there are many options for service status. An individual can begin service as either active duty or active reserves, and many individuals will change from the initial status to another status before completion of the eight year obligation. If an in-
individual enlists in active duty, the active duty portion of the contract can be as short as two years. The remaining obligation can be served in a reserve component or in the inactive ready reserve. Service members joining a reserve component typically are active reservists for a period of at least six years, followed by inactive ready reserve for any remaining time. A service member may opt to re-enlist during their initial (or subsequent) contract, extending their obligation for additional time, beyond the initial eight years.

15 Data

The data used throughout this paper are taken from the American Community Survey (ACS) provided by Integrated Public Use Micro Data Samples (IPUMS) at the University of Minnesota, (Ruggles, Genadek, Goeken, Grover, and Sobek, 2015). The ACS surveys for this paper contain a 1% random sample of the U.S. population for each year from 2000 to 2014. Survey participants change from year to year. Among the survey questions in the ACS is whether the individual served active duty military time during several distinct time intervals: Vietnam Era, 1975-1980, 1980-1990, 1991-2000, 2001-present. Importantly, these data identify individuals who served active military time since 2001 separate from individuals that only served active time pre-2001.

From the sample, I drop individuals younger than 20 years of age since that is the youngest an individual can be upon completion of the active

---

68Individuals that only served in a reserve component but were never activated are indistinguishable from non-veterans. Reported active duty time could have been an overseas deployment or domestic active duty time.
portion of a military contract (without early separation). I also drop individuals over the age of 45 to exclude individuals who were of military age during the Vietnam era; someone who was 45 years old in 2000 would have been 20 in 1975 at the end of the Vietnam war. There is a chance that the resulting sample could include a small number of Vietnam veterans; I drop all veterans who report Vietnam era service time from the sample as well. I also exclude from the ACS anyone who is still on active duty.

All of the veterans in this sample began their military career on a volunteer basis, which creates a selection problem: if individuals choose to volunteer in a systematically and unobserved way, and if the unobserved characteristics that determine military service also affect labor market outcomes, then comparisons between veterans and non-veterans will be biased. The focus of this paper is to compare veterans with one type of experience against veterans with another type of experience; therefore I do not have to address this type of selection.

However, there is a separate type of selection I must address. Since the motivations for, and the consequences of, military service changed so dramatically after 2001, it is probable that the type of person willing to volunteer after 2001 is very different from the type willing to volunteer pre-2001. To the extent that these types are unobserved and correlated with subsequent labor markets outcomes comparisons will again be biased. To address the selection problem, I will compare veterans who report active duty service time between 1990 and 2001 but without post-2001 service to veterans with both 1990-2001 and post-2001 service. Veterans that have both pre and post-2001 service made the decision to join the military
under similar circumstances as veterans with only pre-2001 service time.

This method does not completely address the selection issue; military contracts are for a fixed period of time. A typical initial enlistment contract requires eight years of service, after which the soldier can choose to reenlist or separate from the military. If different types of individuals choose to re-enlist after 2001 systematically along unobserved characteristics, and if those characteristics are correlated with labor market outcomes, selection bias will still be an issue. Empirically however, re-enlistment rates in 2001 and 2002 are very close to the average rate from 1995 to 2002 (Chun, 2005)\textsuperscript{69}, suggesting that this type of selection along unobservables is less relevant.

Tables 9 and 10 describe the ACS data for men and women, respectively, across three subgroups: non-veterans, veterans with service during the 1990 to 2001 period but not since, and individuals with both 1990-2001 service and post 2001 service time. There are significant demographic differences between non-veterans and veterans in terms of racial composition, age and household size. Veterans tend to be older and are more likely to be married than non-veterans. Hispanic individuals are overrepresented, and Asian individuals are underrepresented in the male veteran population. Black females are overrepresented, in the female veteran population while Hispanic and Asian females are underrepresented. However, the differences across types of veterans is much less pronounced.

Age, race, ethnicity and marital status are all very similar across veteran

\textsuperscript{69}For example, among single Army National Guard members with fewer than 7 years of service, retention rates were 59.8 and 64.0 percent in 2001 and 2002, compared to a 1995-2001 average of 62.3. See Chun (2005) for more analysis.
types, those with post-2001 service tend to have, on average, about a half
ty. more schooling. Simply comparing averages, veterans with post-2001
service appear to earn more than veterans with 1990-2001 service and
rates of employment are similar, if slightly lower for recent veterans.

16 Empirical Strategy and Results

The primary goal of this paper is to compare estimates of the labor
market impact of post-2001 military service to voluntary military service
in a prior period. The labor market outcomes I consider are the rate of
employment and earnings, conditional on employment.

16.1 Earnings Conditional on Employment

To measure the effect of post-2001 service on earnings (conditional on
employment) compared to pre-2001 voluntary service, I estimate the fol-
lowing regression separately by gender with the subset of data reporting
positive earnings:

\[
\log Earnings_i = \beta_0 + \beta_1 Vet_i + \beta_2 Vet_{2001i} + \gamma X_i + \delta_t + \epsilon_i
\]

where \(Vet_i\) equals one if individual \(i\) reports active service time between
1990 and 2001, \(Vet_{2001i}\) indicates post-2001 active military service. \(X_i\) is a
vector of demographics including a quadratic for age, controls for race and
ethnicity, marital status, urban residence, and number of children, state
and educational achievement fixed effects. \(\delta_t\) is a year fixed effect. Column
1 of Tables 11 and 12 display the results from this regression for men and
women, respectively. The coefficient on post-2001 service vet represents the earnings premium veterans with post-2001 service time receive, on average, relative to similar veterans without post-2001 service. For men, the earnings premium is 2.8 percent, while for women it is 6.8 percent. Column 2 adds a minority indicator variable interacted with both veteran era-groups. The earnings premium for minority post-2001 male veterans is even higher than that of white post-2001 veterans. The earnings premium for female post-2001 veterans does not appear to be different across race.

16.2 Within and Across Occupations

Military service could increase earnings through several channels. The experience may provide new occupational opportunities that the individual wouldn’t have had it if not for the military service, perhaps the individual was a military police officer which qualifies them for police work as a civilian. On the other hand, some of the pay premium may simply be due to transferable general human capital that makes the individual more productive in the field they would have found themselves in, regardless of service. It could also be the case that employers feel compelled to pay veterans more for a similar position.

In this section, I explore the channel through which post-2001 veterans obtain higher earnings by including occupational fixed effects.\textsuperscript{70} If post-2001 military service increases earnings primarily through occupational opportunities to veterans that would not have been available without post-

\textsuperscript{70}Occupations are defined by rather broad set of 25 categories, examples include: Food Preparation, Financial Specialists, Protective Services.
2001 service (but earn the same as other veterans within the occupation), adding occupational fixed effects would significantly reduce the coefficient estimates for the post-2001 veteran indicator variable. If, on the other hand, post-2001 veterans earn more than other veterans within occupations, then adding occupational will not have meaningfully change the coefficient estimate for the post-2001 veteran indicator.

To examine the channel through which the post-2001 veterans obtain an earnings premium I estimate the following regression with the subset of individuals who report positive earnings:

\[
\log Earnings_i = \beta_0 + \beta_1 Vet_{2001i} + \beta_2 NonWhite_i \cdot Vet_{2001i} + \\
\beta_3 Vet_i + \beta_4 NonWhite_i \cdot Vet_i + \gamma_1 Occupation_i + \gamma_2 X_i + \delta_i + \epsilon_i
\]

Column 3 of Tables 11 and 12 displays the results. Including occupational fixed effects reduces the magnitude of the post-2001 earnings premium by roughly half. Male post-2001 veterans earnings premium within occupation is about 1 percentage point smaller than the estimate without occupational fixed effects for both white and non-white veterans. For females the earnings premium within occupation drops to essentially zero compared to 6.8 percent without regard to occupation. For female post-2001 service members, the earnings premium appears to be linked to occupational opportunity, which does not appear to be the case for male veterans.
16.3 Rate of Employment

I now turn to a different question: do post-2001 veterans tend to be employed at different rates than other veterans whose service ended prior to 2001? As discussed above, veterans who serve post-2001 are at a higher risk of long deployments compared to those who served in prior periods. These long deployments interrupt the civilian labor market experience for active and inactive reservists. Those returning from a long overseas deployment are also at a higher risk of returning with physical or mental disability. On the other hand, employment programs exist to assist veterans with employment, potentially countering some of the negative effects of a long deployment. To explore the effect of post-2001 service on employment rates I estimate the following regression on the full sample:

\[
Employed_i = \beta_0 + \beta_1 Vet_i + \beta_2 Vet_{2001_i} + \gamma X_i + \delta_i + \varepsilon_i
\]

where \( Employed_i \) equals 1 if the individual reports current employment. The veteran indicator variable and the vector containing control variables, \( X_i \), are the same as in sections 16.1 and 16.2. Column 4 of Tables 11 and 12 display the results of this regression and Column 5 includes an indicator variable for minority, interacted with veteran type. Relative to other veterans, male veterans with post-2001 are 2.1 percentage points less likely to be employed. However, the results in column (5) suggest that the reduction in employment is only apparent for white males, non-white males with post-2001 are employed at the same rate as comparable veterans with earlier service time. Female post-2001 veterans are 4.1 per-
centage points less likely to be employed, and as shown in Column 5, this result is regardless of race. Previous literature suggests that post-Vietnam era veterans are employed at lower rates (Faberman and Foster, 2013, Humensky, Jordan, Stroupe, and Hynes, 2013, Kleykamp, 2013). Columns 4 and 5 in Tables 11 and 12 reinforce this notion and suggest that specifically those that served post-2001 are employed at even lower rates.

16.4 Robustness to Alternative Samples

The sample used in sections 16.1-16.2 contains veterans with post-2001 and 1990-2001 service and veterans with 1990-2001 service but not post-2001 service. However both sets contained service members with pre-1990 service. In this section I estimate the same regressions as above with alternative samples that may provide more similar control and treatment groups, at the cost of a smaller sample size.

One potential issue with the baseline sample is that if one compares veterans in the same year across these two veteran types, veterans with post-2001 service will, by construction, have more recently separated from the military. Veterans with post-2001 service separated from the military sometime between 2001 and 2013, veterans without post-2001 service separated sometime between 1990-2001. It is possible that the results above are picking up the effect of more recently being an active duty soldier as opposed to anything specific about the post-2001 service.

To control for time since separation I restrict the data to 2000-2004 and 2010-2014. I also drop post-2001 veterans from the 2000-2004 era so that the only veterans in the early sample are veterans with 1990-2001 service.
but without post-2001 service. I also drop veterans without post-2001 service from the latter period. Then I create a wave variable to identify the year within the sub-sample, specifically the wave variable equals 1 in both 2000 and 2010, 2 in both 2001 and 2011, 3 in both 2002 and 2012 and so on. This way post-2001 veterans interviewed in 2010 are being compared to veterans without post-2001 service interviewed in 2000, the idea being that these two types of veterans will have been separated from the military for a comparable amount of time. The rest of the control variables remain the same as previous regressions including the time fixed effects. Since the data in this specification do not have pre and post-2001 veterans in any given year, the year fixed effects – and the evolution of real wages – are calibrated by non-veterans in each year.

Column 2 of Tables 13 and 14 display results for these wage regression, Column 2 of Tables 15 and 16 contain results for the employment regressions. Generally speaking, many of same conclusions can be drawn from this regression as from the regressions using the full sample. Post-2001 veterans tend to earn more than, and tend to be under employed relative to veterans without post-2001 service. There are some differences though, the earnings premium for male post-2001 veterans appears not to depend on race for this sample, and is of similar magnitude to the earnings premium estimated for minority post-2001 veterans from the baseline sample. The earnings premium estimate for female post-2001 veterans declines with this sample but is less precisely estimated. Estimates of post-2001 service effects on employment (Tables 15 and 16) are slightly smaller for males but nearly identical for females.
Column 3 in Tables 13 - 16 restrict the baseline sample to only veterans. Results for female veterans are nearly identical to that of the baseline sample. For males, the earnings again is heterogenous across race while the employment results are nearly identical.

Another potential issue with comparing veterans with post-2001 service against veterans without post-2001 service is that those with post-2001 service likely enlisted more recently. Indeed, veterans without post-2001 service report military service between 1980-1990 more often than post-2001 veterans. In an attempt to align enlistment dates I reduce the baseline sample to exclude veterans with pre-1990 military service. Columns 4 - 6 of Tables 13 - 16 display analogous regressions to the first three columns, using the sample that excludes veterans with pre-1990 service.

The employment regressions – Tables 15 and 16 – are quite robust to sample choice, white male and female post-2001 veterans appear to be underemployed while minority male post-2001 veterans appear to be employed at the same rate as comparable veterans without post-2001 service. The wage regressions – Tables 13 and 14 – on the other hand, are less robust to these alternate specifications. Specifically, estimates in Column 5 suggest little to no earnings premium for veterans with post-2001 service over similar veterans without post-2001 service. Although these coefficients are estimated with less certainty; one could not rule out effects of a size similar to the other specifications for men, and small positive wage premia for women.
17 Conclusion

The military experience in the United States changed dramatically after 2001. Military utilization rates increased dramatically with the onset of wars in Afghanistan and Iraq. This paper provides evidence that veterans with service time after 2001 tend to be underemployed compared to similar veterans without service after 2001. However, conditional on employment, post-2001 veterans earn at least as much as over veterans without post-2001 service. This wage premium is greater for minority men and for women, regardless of race. When controlling for occupation, the estimated wage gap between veterans and non-veterans declines suggesting occupational opportunities created by military experience may be the important channel propagating wage premium.

The results across gender are different in some important ways. Overall, wage premiums for female pre and post-2001 veterans are much larger than for men. While some of the earnings boost for veterans without post-2001 service is explained by minority earnings, minority status seems to have little effect for female veterans with post-2001 service. Furthermore, occupational fixed effects explain nearly all of the wage premium for female post-2001 veterans, suggesting that occupational opportunities afforded by post-2001 service is an important channel through which these veterans are increasing their earnings. Female post-2001 veterans are underemployed to a much greater degree than for males.

Overall this paper provides evidence that the labor market experience for veterans with post-2001 service is fundamentally different than comparable veterans without post-2001 service. Furthermore, this paper pro-
vides evidence that the labor market experience is quite different for female veterans than for male veterans.
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<td>0.481</td>
<td>0.639</td>
<td>0.688</td>
</tr>
<tr>
<td>Age</td>
<td>32.73</td>
<td>36.09</td>
<td>35.92</td>
</tr>
<tr>
<td>Years of education</td>
<td>13.15</td>
<td>13.54</td>
<td>14.00</td>
</tr>
<tr>
<td>Black</td>
<td>0.107</td>
<td>0.129</td>
<td>0.126</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.164</td>
<td>0.0813</td>
<td>0.0923</td>
</tr>
<tr>
<td>Asian</td>
<td>0.0606</td>
<td>0.0235</td>
<td>0.0316</td>
</tr>
<tr>
<td>Lives in City</td>
<td>0.353</td>
<td>0.285</td>
<td>0.352</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>5513416</td>
<td>184102</td>
<td>46453</td>
</tr>
</tbody>
</table>

**Notes:** Data include the 1 percent ACS samples from 2000 to 2014. The sample is restricted to men aged 20-45 who are not full time students nor currently an active military service member. The first column summarizes data for non-veterans. The second column summarizes data for veterans who report active service between 1990 and 2001 but not after 2001. The third column summarizes data for veterans who report active service time both during during the 1990 to 2001 period and after 2001. Earnings are reported in real 2010 dollars.
Table 10: Variable Means for Women (2000-2014)

<table>
<thead>
<tr>
<th></th>
<th>Non-veterans</th>
<th>'90-'01 Service</th>
<th>'90-'01 and Post-'01 Service</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real Wage Earnings</td>
<td>23430.5</td>
<td>29713.8</td>
<td>34206.9</td>
</tr>
<tr>
<td>Real Wage Earnings (cond on pos)</td>
<td>31036.6</td>
<td>36785.2</td>
<td>42179.2</td>
</tr>
<tr>
<td>Employed</td>
<td>0.694</td>
<td>0.729</td>
<td>0.698</td>
</tr>
<tr>
<td>Female</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Children at home</td>
<td>0.567</td>
<td>0.678</td>
<td>0.660</td>
</tr>
<tr>
<td>Married</td>
<td>0.540</td>
<td>0.574</td>
<td>0.604</td>
</tr>
<tr>
<td>Age</td>
<td>33.10</td>
<td>35.53</td>
<td>34.79</td>
</tr>
<tr>
<td>Years of education</td>
<td>13.58</td>
<td>14.03</td>
<td>14.57</td>
</tr>
<tr>
<td>Black</td>
<td>0.117</td>
<td>0.216</td>
<td>0.229</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.148</td>
<td>0.0797</td>
<td>0.0994</td>
</tr>
<tr>
<td>Asian</td>
<td>0.0640</td>
<td>0.0286</td>
<td>0.0398</td>
</tr>
<tr>
<td>Lives in City</td>
<td>0.355</td>
<td>0.293</td>
<td>0.379</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>6112929</td>
<td>34432</td>
<td>9756</td>
</tr>
</tbody>
</table>

Notes: Data include the 1 percent ACS samples from 2000 to 2014. The sample is restricted to women aged 20-45 who are not full time students nor currently an active military service member. The first column summarizes data for non-veterans. The second column summarizes data for veterans who report active service between 1990 and 2001 but not after 2001. The third column summarizes data for veterans who report active service time both during the 1990 to 2001 period and after 2001. Earnings are reported in real 2010 dollars.
Table 11: Male Veterans with 1990-2001 Service

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Post-2001 Veteran</strong></td>
<td>0.028</td>
<td>0.021</td>
<td>0.012</td>
<td>-0.021</td>
<td>-0.025</td>
</tr>
<tr>
<td></td>
<td>(0.0050)***</td>
<td>(0.0055)***</td>
<td>(0.0053)**</td>
<td>(0.0020)***</td>
<td>(0.0022)***</td>
</tr>
<tr>
<td><strong>Minority Post-2001 Vet</strong></td>
<td>0.042</td>
<td>0.034</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.013)***</td>
<td>(0.013)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Veteran</strong></td>
<td>0.050</td>
<td>0.041</td>
<td>0.015</td>
<td>-0.0011</td>
<td>-0.0070</td>
</tr>
<tr>
<td></td>
<td>(0.0023)***</td>
<td>(0.0025)***</td>
<td>(0.0025)***</td>
<td>(0.00092)***</td>
<td>(0.0010)***</td>
</tr>
<tr>
<td><strong>Minority Veteran</strong></td>
<td>0.051</td>
<td>0.059</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0060)***</td>
<td>(0.0058)***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4783218</td>
<td>4783218</td>
<td>4783218</td>
<td>5743971</td>
<td>5743971</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.354</td>
<td>0.354</td>
<td>0.394</td>
<td>0.129</td>
<td>0.129</td>
</tr>
</tbody>
</table>

**Notes:** (*) $P<.10$, (** $P<.05$, (***) $P<.01$) Data include the 1 percent ACS samples from 2000 to 2010. The sample is restricted to men aged 20-45 who are not full time students nor currently an active military service member. The dependent variable in Column 1 is log wages and the sample is restricted to those with positive earnings. Independent variables include veteran status and control variables: a quadratic for age, controls for race and ethnicity, marital status, urban residence, and fixed effects for number of children, state, year and educational achievement. Column 2 interacts an indicator variable for individuals whose race is not white with veteran status. Column 3 includes occupational fixed effects. The dependent variable in Column 4 is employment. Column 5 interacts an indicator variable for individuals whose race is not white with veteran status.
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Post-2001 Veteran</td>
<td>0.068</td>
<td>0.065</td>
<td>0.016</td>
<td>-0.041</td>
<td>-0.041</td>
</tr>
<tr>
<td></td>
<td>(0.013)***</td>
<td>(0.015)***</td>
<td>(0.015)</td>
<td>(0.0051)***</td>
<td>(0.0060)***</td>
</tr>
<tr>
<td>Minority Post-2001 Vet</td>
<td>0.0067</td>
<td>-0.0066</td>
<td></td>
<td></td>
<td>-0.0022</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.028)</td>
<td></td>
<td></td>
<td>(0.011)</td>
</tr>
<tr>
<td>Veteran</td>
<td>0.080</td>
<td>0.062</td>
<td>0.015</td>
<td>-0.0062</td>
<td>-0.019</td>
</tr>
<tr>
<td></td>
<td>(0.0062)***</td>
<td>(0.0072)***</td>
<td>(0.0070)**</td>
<td>(0.0024)***</td>
<td>(0.0028)***</td>
</tr>
<tr>
<td>Minority Veteran</td>
<td>0.064</td>
<td>0.066</td>
<td></td>
<td></td>
<td>0.047</td>
</tr>
<tr>
<td></td>
<td>(0.014)***</td>
<td>(0.013)***</td>
<td></td>
<td></td>
<td>(0.0054)***</td>
</tr>
<tr>
<td>Observations</td>
<td>4650557</td>
<td>4650557</td>
<td>4650557</td>
<td>6157117</td>
<td>6157117</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.239</td>
<td>0.239</td>
<td>0.295</td>
<td>0.078</td>
<td>0.078</td>
</tr>
</tbody>
</table>

Notes: (*) $P < .10$, (**) $P < .05$, (***) $P < .01$ Data include the 1 percent ACS samples from 2000 to 2010. The sample is restricted to women aged 20-45 who are not full time students nor currently an active military service member. The dependent variable in Column 1 is log wages and the sample is restricted to those with positive earnings. Independent variables include veteran status and control variables: a quadratic for age, controls for race and ethnicity, marital status, urban residence, and fixed effects for number of children, state, year and educational achievement. Column 2 interacts an indicator variable for individuals whose race is not white with veteran status. Column 3 includes occupational fixed effects. The dependent variable in Column 4 is employment. Column 5 interacts an indicator variable for individuals whose race is not white with veteran status.
Table 13: Robustness to Alternative Samples: Wages Men

<table>
<thead>
<tr>
<th></th>
<th>90-01 Service</th>
<th></th>
<th></th>
<th>Start 90-01</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adj</td>
<td>Vets</td>
<td>Adj</td>
<td>Vets</td>
<td>Adj</td>
<td>Vets</td>
</tr>
<tr>
<td>Post-2001 Veteran</td>
<td>0.021</td>
<td>0.070</td>
<td>-0.0092</td>
<td>0.031</td>
<td>0.015</td>
<td>0.0087</td>
</tr>
<tr>
<td></td>
<td>(0.0055)***</td>
<td>(0.0088)***</td>
<td>(0.0050)</td>
<td>(0.0065)***</td>
<td>(0.010)</td>
<td>(0.0062)</td>
</tr>
<tr>
<td>Minority Post-2001 Vet</td>
<td>0.042</td>
<td>-0.0074</td>
<td>0.047</td>
<td>0.046</td>
<td>-0.0047</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>(0.013)***</td>
<td>(0.021)</td>
<td>(0.011)***</td>
<td>(0.016)***</td>
<td>(0.024)</td>
<td>(0.014)***</td>
</tr>
<tr>
<td>Veteran</td>
<td>0.041</td>
<td>0.012</td>
<td>–</td>
<td>0.044</td>
<td>0.057</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>(0.0025)***</td>
<td>(0.0048)***</td>
<td>–</td>
<td>(0.0030)***</td>
<td>(0.0060)***</td>
<td>–</td>
</tr>
<tr>
<td>Minority Veteran</td>
<td>0.051</td>
<td>0.083</td>
<td>–</td>
<td>0.047</td>
<td>0.069</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>(0.0060)***</td>
<td>(0.011)***</td>
<td>–</td>
<td>(0.0070)***</td>
<td>(0.013)***</td>
<td>–</td>
</tr>
<tr>
<td>Observations</td>
<td>4783218</td>
<td>2829221</td>
<td>206778</td>
<td>4724169</td>
<td>2809136</td>
<td>147729</td>
</tr>
<tr>
<td>R^2</td>
<td>0.354</td>
<td>0.354</td>
<td>0.192</td>
<td>0.354</td>
<td>0.354</td>
<td>0.187</td>
</tr>
</tbody>
</table>

Notes: (* P<.10, ** P<.05, *** P<.01) All columns are regressions with the log of wages as the dependent variable. Independent variables include veteran status and control variables: a quadratic for age, controls for race and ethnicity, marital status, urban residence, and fixed effects for number of children, state, year and educational achievement. Column 1 is the baseline regression from Table 11, provided here for reference. Column 2 restricts data to two time periods: 2000-2004 and 2010-2014. The only veterans included in the 2000-2004 period are those without post-2001 service. The only veterans included in the 2010-2014 period are veterans with post-2001 service time. Column 3 uses the same sample as the baseline specification in Column 1 but drops nonveterans. Columns 4 - 6 are analogous to Columns 1 - 3 but drop any veterans with active service prior to 1990.
Table 14: Robustness to Alternative Samples: Wages Women

<table>
<thead>
<tr>
<th></th>
<th>90-01 Service</th>
<th>Start 90-01</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adj</td>
<td>Vets</td>
</tr>
<tr>
<td>Post-2001 Veteran</td>
<td>0.065 (0.015)**</td>
<td>0.040 (0.024)</td>
</tr>
<tr>
<td>Minority</td>
<td>0.0067 (0.029)</td>
<td>-0.022 (0.046)</td>
</tr>
<tr>
<td>Post-2001 Vet</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Veteran</td>
<td>0.062 (0.0072)**</td>
<td>0.057 (0.013)**</td>
</tr>
<tr>
<td>Minority Veteran</td>
<td>0.064 (0.014)**</td>
<td>0.13 (0.025)**</td>
</tr>
<tr>
<td>Observations</td>
<td>4650557</td>
<td>2790791</td>
</tr>
<tr>
<td>R²</td>
<td>0.239</td>
<td>0.244</td>
</tr>
</tbody>
</table>

Notes: (* P<.10, ** P<.05, *** P<.01) All columns are regressions with the log of wages as the dependent variable. Independent variables include veteran status and control variables: a quadratic for age, controls for race and ethnicity, marital status, urban residence, and fixed effects for number of children, state, year and educational achievement. Column 1 is the baseline regression from Table 12, provided here for reference. Column 2 restricts data to two time periods: 2000-2004 and 2010-2014. The only veterans included in the 2000-2004 period are those without post-2001 service. The only veterans included in the 2010-2014 period are veterans with post-2001 service time. Column 3 uses the same sample as the baseline specification in Column 1 but drops nonveterans. Columns 4 - 6 are analogous to Columns 1 - 3 but drop any veterans with active service prior to 1990.

Table 15: Robustness to Alternative Samples: Employment Men

<table>
<thead>
<tr>
<th></th>
<th>90-01 Service</th>
<th>Start 90-01</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adj</td>
<td>Vets</td>
</tr>
<tr>
<td>Post-2001 Veteran</td>
<td>-0.025 (0.0022)**</td>
<td>-0.012 (0.0035)**</td>
</tr>
<tr>
<td>Minority</td>
<td>0.023 (0.0052)**</td>
<td>0.014 (0.0083)</td>
</tr>
<tr>
<td>Post-2001 Vet</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Veteran</td>
<td>-0.0070 (0.0010)**</td>
<td>-0.016 (0.0020)**</td>
</tr>
<tr>
<td>Minority Veteran</td>
<td>0.032 (0.0023)**</td>
<td>0.038 (0.0044)**</td>
</tr>
<tr>
<td>Observations</td>
<td>5743971</td>
<td>3446197</td>
</tr>
<tr>
<td>R²</td>
<td>0.129</td>
<td>0.134</td>
</tr>
</tbody>
</table>

Notes: (* P<.10, ** P<.05, *** P<.01) All columns are regressions with employment status as the dependent variable. Independent variables include veteran status and control variables: a quadratic for age, controls for race and ethnicity, marital status, urban residence, and fixed effects for number of children, state, year and educational achievement. Column 1 is the baseline regression from Table 11, provided here for reference. Column 2 restricts data to two time periods: 2000-2004 and 2010-2014. The only veterans included in the 2000-2004 period are those without post-2001 service. The only veterans included in the 2010-2014 period are veterans with post-2001 service time. Column 3 uses the same sample as the baseline specification in Column 1 but drops nonveterans. Columns 4 - 6 are analogous to Columns 1 - 3 but drop any veterans with active service prior to 1990.
Table 16: Robustness to Alternative Samples: Employment Women

<table>
<thead>
<tr>
<th></th>
<th>90-01 Service</th>
<th>Start 90-01</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adj</td>
<td>Vets</td>
</tr>
<tr>
<td>Post-2001 Veteran</td>
<td>-0.041</td>
<td>-0.042</td>
</tr>
<tr>
<td>Minor</td>
<td>-0.0022</td>
<td>0.029</td>
</tr>
<tr>
<td>Post-2001 Vet</td>
<td>(0.011)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Veteran</td>
<td>-0.019</td>
<td>-0.024</td>
</tr>
<tr>
<td>Minority Veteran</td>
<td>0.047</td>
<td>0.038</td>
</tr>
<tr>
<td>Observations</td>
<td>6157117</td>
<td>3726490</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.078</td>
<td>0.080</td>
</tr>
</tbody>
</table>

Notes: (* P<.10, ** P<.05, *** P<.01) All columns are regressions with employment status as the dependent variable. Independent variables include veteran status and control variables: a quadratic for age, controls for race and ethnicity, marital status, urban residence, and fixed effects for number of children, state, year and educational achievement. Column 1 is the baseline regression from Table 12, provided here for reference. Column 2 restricts data to two time periods: 2000-2004 and 2010-2014. The only veterans included in the 2000-2004 period are those without post-2001 service. The only veterans included in the 2010-2014 period are veterans with post-2001 service time. Column 3 uses the same sample as the baseline specification in Column 1 but drops nonveterans. Columns 4 - 6 are analogous to Columns 1 - 3 but drop any veterans with active service prior to 1990.
Theoretical Appendix to Chapter II

The Lagrangian associated to the government’s program writes:

\[ \Lambda(t) \overset{\text{def}}{=} \sum_{i=1}^{l} (T_i + b) \mathcal{H}_i(t) - b - E + \frac{1}{\lambda} \Omega(\mathcal{\Psi}_1(t), ..., \mathcal{\Psi}_l(t), u(b)) \]  

(26)

18 Derivation of Equations (14) and (15)

Differentiating (26) with respect to \( T_j \) and using Equations (10) and (13) gives (14). Differentiating (26) with respect to \( b \) gives:

\[ \frac{\partial \Lambda}{\partial b} = -1 + \sum_{i=1}^{l} h_i + \sum_{i=1}^{l} (T_i + b) \frac{\partial \mathcal{H}_i}{\partial b} + \frac{u'(b) \partial \Omega}{\lambda \partial b} + \sum_{i=1}^{l} \frac{\partial \mathcal{\Psi}_i}{\partial b} \frac{\partial \Omega}{\partial \mathcal{\Psi}_i} \]

Differentiating \( \mathcal{\Psi}_i(t) \equiv \mathcal{P}_i(t) (u(\mathcal{C}_i(t)) - d_i) + (1 - \mathcal{P}_i(t)) u(b) \) with respect to \( b \) gives:

\[ \frac{\partial \mathcal{\Psi}_i}{\partial b} = (1 - p_i) u'(b) + p_i u'(c_i) \left[ \frac{\partial \mathcal{C}_i}{\partial b} + \frac{\partial \mathcal{P}_i u(c_i) - d_i - b}{\partial b} \right] \]

Using \( h_0 = 1 - \sum_{i=1}^{l} h_i \) and Equations (13) and (16) leads to (15). From \( \frac{\partial \mathcal{C}_i}{\partial T_j} = \frac{\partial \mathcal{\Psi}_i}{\partial T_j} - 1 \) and for \( j \neq i \), \( \frac{\partial \mathcal{C}_i}{\partial T_i} = \frac{\partial \mathcal{\Psi}_i}{\partial T_i} \), the sum of (14) for all \( T_j \) minus Equation (15) leads to:

\[ 0 = \sum_{i=1}^{l} h_i + \sum_{i=1}^{l} (T_i + b) \left( \sum_{j=1}^{l} \frac{\partial \mathcal{H}_i}{\partial T_j} - \frac{\partial \mathcal{H}_i}{\partial b} \right) - \left( g_0 h_0 + \sum_{i=1}^{l} g_i h_i \right) \]

(27)

\[ + \sum_{i=1}^{l} g_i h_i \left( \sum_{j=1}^{l} \frac{\partial \mathcal{\Psi}_i}{\partial T_j} - \frac{\partial \mathcal{\Psi}_i}{\partial b} \right) + \sum_{i=1}^{l} g_i h_i \frac{u(c_i) - d_i - u(b)}{u'(c_i)} \left( \sum_{j=1}^{l} \frac{\partial \mathcal{P}_i}{\partial T_j} - \frac{\partial \mathcal{P}_i}{\partial b} \right) \]
In the absence of income effects, a simultaneous change in all tax liabilities and welfare benefit $\Delta T_1 = \ldots = \Delta T_i = -\Delta b$ induces no changes in wages, conditional employment probabilities not employment levels, so that $\sum_{i=1}^I \frac{\partial w_i}{\partial T_i} = \ldots = \sum_{i=1}^I \frac{\partial \rho_i}{\partial T_i} = \sum_{i=1}^I \frac{\partial h_i}{\partial T_i} = \frac{\partial h_i}{\partial b}$. Plugging these equalities in (27) leads to: $g_0 h_0 + \sum_{i=1}^I g_i h_i = 1$.

### 18.1 Derivation of Equation (19)

Let $A$ denotes the square matrix of rank $I$ whose term in row $j$ and column $i$ is $\frac{\partial c_i}{\partial T_j} + \frac{\partial \rho_i}{\partial T_j} \frac{u(c_i) - d_i - u(b)}{p_i u'(c_i)}$. The optimal tax formula (14) can be rewritten in matrix notations:

$$
0 = \begin{cases} h \begin{cases} \text{Mechanical effect} \\ \text{Behavioral effects} \\ \text{Social Welfare effects} \end{cases} + \frac{dH}{dT} \begin{pmatrix} T + b \end{pmatrix} + A \cdot \begin{pmatrix} gh \end{pmatrix} \end{cases} \tag{28}
$$

However, Equation (10) implies that: $\frac{d\psi}{dT} = -A \cdot \frac{d\psi}{dT}^{\text{Micro}}$. Moreover, from $K_i(t) = \hat{K}_i(\psi(t))$, we get that: $\frac{dK}{dT} = \frac{d\psi}{dT} \cdot \frac{d\hat{K}}{d\psi}$ and $\frac{dK}{dT}^{\text{Micro}} = \frac{d\psi}{dT}^{\text{Micro}} \cdot \frac{d\hat{K}}{d\psi}$. We thus get that:

$$
-A = \frac{d\psi}{dT} \cdot \left( \frac{d\psi}{dT}^{\text{Micro}} \right)^{-1} = \frac{dK}{dT} \cdot \left( \frac{dK}{dT}^{\text{Micro}} \right)^{-1}
$$

whenever $\frac{d\hat{K}}{d\psi}$ is invertible, in which case Equation (28) can be rewritten as (19).
19 The Matching model

We consider a matching economy where on each labor market $i$, the constant returns to scale matching function gives the employment level $h_i$ as a function $M_i(v_i, k_i)$ of the number $v_i$ of vacancies posted and the number $k_i$ of participating job seekers (Pissarides and Petrongolo, 2001). Creating a job costs $\kappa_i > 0$ and generates output $y_i > \kappa_i$ when a worker is recruited. Hence, the different types of labor are perfect substitutes.

Each vacancy is matched with probability $q_i = Q_i(\theta_i) \overset{\text{def}}{=} \frac{M_i(v_i, k_i)}{v_i} = M_i(1, 1/\theta_i)$, which is decreasing in tightness $\theta_i \overset{\text{def}}{=} v_i/k_i$. Firms create jobs whenever the expected profit $q_i(y_i - w_i) - \kappa_i$ is positive. As more vacancies are created, tightness decreases until the free entry condition $q_i(y_i - w_i) = \kappa_i$ is verified. The conditional employment probability is an increasing function of tightness through $p_i = P(\theta_i) \overset{\text{def}}{=} \frac{M_i(v_i, k_i)}{k_i} = M_i(\theta_i, 1)$.

Therefore, the conditional probability $p_i$ is a decreasing function of the gross wage through $p_i = P_i \left( Q_i^{-1} \left( \frac{\kappa_i}{y_i - w_i} \right) \right)$, which determines the labor demand function $p_i = \mathcal{L}_i(w_i)$.

Under risk neutrality and proportional bargaining (20), one has for any $j \neq i$ that $\frac{\partial y_i}{\partial T_j} = 0$, thereby $\frac{\partial P_i}{\partial T_j} = 0$ from $p_i = \mathcal{L}_i(w_i)$, and finally $\frac{\partial y_i}{\partial T_i} = 0$ from (10). Moreover, we get from $p_i = \mathcal{L}_i(w_i)$ and (10) that:

$$\frac{\partial \mathcal{U}_i}{\partial T_i} = \left[ -1 + \frac{\partial \mathcal{W}_i}{\partial T_i} \left( 1 + \frac{w_i \partial \mathcal{P}_i}{p_i \partial w_i} \left( w_i - T_i - d_i - b \right) \right) \right] p_i$$

As $\mu_i \in (0, 1)$ denote the elasticity of the matching function with respect to the number of job-seekers, we get $\frac{dp_i}{p_i} = (1 - \mu_i) \frac{d\theta_i}{\theta_i}$ and $\frac{d\theta_i}{q_i} = -\mu_i \frac{d\theta_i}{\theta_i}$, so $\frac{dp_i}{p_i} = -1 - \frac{\mu_i}{q_i} \frac{d\theta_i}{q_i}$. Log-differentiating the free-entry condition $k_i = q_i \left( y_i - w_i \right)$
leads to \( \frac{dq_i}{q_i} = \frac{w_i}{y_i - w_i} \frac{dw_i}{w_i} \). So, we get \( \frac{dp_i}{p_i} = -\frac{1 - \mu_i}{\mu_i} \frac{w_i}{y_i - w_i} \frac{dw_i}{w_i} \), i.e.: \( \frac{w_i}{p_i} \frac{\partial p_i}{\partial w_i} = -\frac{1 - \mu_i}{\mu_i} \frac{w_i}{y_i - w_i} \)

and:

\[
\frac{\partial \mathcal{U}_i}{\partial T_i} = \left[-1 + \frac{\partial \mathcal{W}_i}{\partial T_i} \left(1 - \frac{1 - \mu_i}{\mu_i} \frac{w_i - T_i - d_i - b}{y_i - w_i}\right)\right] p_i
\]

Equation (20) implying that \( \frac{w_i - T_i - d_i - b}{y_i - w_i} = \frac{\beta_i}{1 - \beta_i} \) and \( \frac{\partial \mathcal{W}_i}{\partial T_i} = 1 - \beta_i \), we get:

\[
\frac{\partial \mathcal{U}_i}{\partial T_i} = \left[-1 + (1 - \beta_i) \left(1 - \frac{1 - \mu_i}{\mu_i} \frac{\beta_i}{1 - \beta_i}\right)\right] p_i = \frac{\beta_i}{\mu_i} \frac{\partial \mathcal{U}_i}{\partial T_i} \]

(29)

when \( \mu_i > 0 \) and \( \beta_i < 1 \), which ends the proof of Proposition 3.
Online Appendix to Chapter II

20 Theory

20.1 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 \( \frac{dp}{dt} = 0 \)) 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 \( F(h_1, ..., h_I, Z) \).\(^{71}\) 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, Michaillat, and Saez (2015) which are plausible in the short run.

We then get that:

**Proposition 4.** If the unemployment rates are exogenous, the production function exhibits constant returns to scale and \( \frac{dF}{dt} \) is invertible, the optimal

\(^{71}\)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.
tax schedule is given by:

\[ 0 = (1 - g_j)h_j + \sum_{i=1}^{I} (T_i + b) \left. \frac{\partial H_i}{\partial T_j} \right|^{\text{Micro}} \]

(30)

and depends only on microeconomic employment responses.

**Proof:** In the absence of unemployment responses to taxation \( \frac{\partial P_i}{\partial T_j} = 0 \), the matrix \( A \) of corrective terms \( \frac{\partial C_i}{\partial T_j} + \frac{\partial P_i}{\partial T_j} \frac{u(c_i) - u(d_i) - u(b)}{p_i u' (c_i)} \) coincides with \( \frac{\partial \varphi}{\partial T} \). We thus get: \( \frac{dK}{dT} = - \frac{d\varphi}{dT} \cdot \frac{dK}{dT} \) Micro and \( \frac{dH}{dT} = - \frac{d\varphi}{dT} \cdot \frac{dH}{dT} \) Micro. Equation (14) then successively leads to:

\[
0 = h - \left( \frac{d\varphi}{dT} \right)^{-1} \cdot \left( \frac{dK}{dT} \right)^{\text{Micro}} \cdot (T + b) + \frac{d\varphi}{dT} \cdot \frac{dK}{dT} \cdot \left( \left. \frac{dK}{dT} \right|^{\text{Micro}} \right)^{-1} \cdot (g \ h) \\
0 = h - \left( \frac{d\varphi}{dT} \right)^{-1} \cdot \left( \frac{dH}{dT} \right)^{\text{Micro}} \cdot (T + b) + \frac{d\varphi}{dT} \cdot (g \ h) \\
0 = \left( \frac{d\varphi}{dT} \right)^{-1} \cdot h - \left. \frac{dH}{dT} \right|^{\text{Micro}} \cdot (T + b) + g \ h 
\]

(31)

where the last equality requires the matrix \( \frac{d\varphi}{dT} \) to be invertible.

Moreover, the firm’s profit function verifies

\[ \Pi(w_1, ..., w_I, r) \overset{\text{def}}{=} \max_{h_1, ..., h_I, Z} F(h_1, ..., h_I, Z) - \sum_{i=1}^{I} w_i h_i - r Z. \]

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 the assumption of an inelastic return of capital leads to \( 0 = \sum_{i=1}^{I} h_i \frac{\partial w_i}{\partial T_j} \). In matrix notation, this implies that \( h \) is an eigenvector of Matrix \( \frac{d\varphi}{dT} \) associated to eigenvalue \( 0 \). Hence, \( h \) is an eigenvector of Matrix \( \frac{d\varphi}{dT} \) associated to eigenvalue \( -1 \), so \( \frac{d\varphi}{dT} \cdot h = -h \) and eventually
\[
\left( \frac{d\mu}{dT} \right)^{-1} \cdot h = -h. \text{ Therefore Equation (31) simplifies to:}
\]

\[
0 = 1 - gh + \left. \frac{dH}{dT} \right|_{\text{Micro}} \cdot (T + b)
\]

which corresponds to (30).

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.

21 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 \( t_0 \). The corresponding density weights in the observed economy are given as \( h_i^0 = \mathcal{H}_i(t_0) \).

21.1 System of Equations

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

\[
 b + E = \sum_{i=1}^{I} (T_i + b) \mathcal{H}_i(t) \tag{32}
\]

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:

\[
 (1 - g_i)h_i + g_ih_i \left. \frac{\partial K_k}{\partial T_i} \right|_{w,p} - \left. \frac{\partial K_k}{\partial T_i} \right|_{w,p} = -(T_i + b) \frac{\partial \mathcal{H}_i}{\partial T_i} \tag{33}
\]

for \( i = 1, \ldots, I \).
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:

$$0 = -(1 - g_0)h_0 + \sum_{j=1}^{I}(T_j + b) \frac{\partial H_j}{\partial b}$$  \hspace{1cm} (34)$$

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 $g_i = \frac{1}{1 + c_i}$ 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 $c_i = w_i(t) - T_i$, 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 $c_i = w_i(t_0) - T_i$.

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

$$h_i = h_i^0 + \frac{\partial H_i}{\partial T_i} (T_i - T_i^0) + \frac{\partial H_i}{\partial b} (b_i - b_i^0)$$ \hspace{1cm} (35)$$

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

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21.2 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:

$$\frac{\partial c_j}{\partial b} = \frac{\partial w_j}{\partial b} = \frac{\partial p_j}{\partial b} = 0$$

(36)

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

$$0 = -h_0 + \sum_{j=1}^{l} (T_j + b) \frac{\partial H_j}{\partial b} + g_0 k_0 + \sum_{j=1}^{l} g_j h_j \left[ \frac{1 - p_j u'(b)}{p_j u'(c_j)} \right]$$

(37)

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 (37) becomes:

$$0 = -h_0 + \sum_{j=1}^{l} (T_j + b) \frac{\partial H_j}{\partial b} + g_0 k_0 + \sum_{j=1}^{l} g_0 k_j [1 - p_j]$$

$$= -(1 - g_0) h_0 + \sum_{j=1}^{l} (T_j + b) \frac{\partial H_j}{\partial b}$$

(38)
22 Description of Data Sources and Cleaning Steps

22.1 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 de-
mographic characteristics and annual income, among others.\textsuperscript{72} 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 in March, with the remaining observations (from the ORG) being equally distributed across the remaining months.\textsuperscript{73}

\textsuperscript{72}While questions about labor force status (the \textit{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 \textit{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.

\textsuperscript{73}From 1984 to 1993 we only have data from the March Supplement, so all observations
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.\textsuperscript{74}

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.\textsuperscript{75}

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.

\textbf{22.2 Data Cleaning}

\textbf{22.2.a CPS Data}

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

\textsuperscript{74}We sometimes refer to the AFDC/TANF and food stamps programs as “welfare” programs.

\textsuperscript{75}See Feenberg and Coutts (1993) for a detailed description of the TAXSIM software.
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 \textit{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 \textit{momloc} variable would be equal to “00”; if the mother is the head of household, the value of the \textit{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 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 be-
 tween 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 re-
strict 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 mil-
tary (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 Sup-
plement only) indicates the number of weeks the respondent worked for
pay in the previous year. The incwage (also available in the March Supple-
ment only) variable captures the respondent’s reported pre-tax earnings.\footnote{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.}
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.

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**22.2.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.\textsuperscript{77} Respondents in each SIPP panel are interviewed every four months (a wave) for a two to four years.\textsuperscript{78} 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 \textit{age} in the 1990 to 1993 SIPP panels, but is called \textit{tage} beginning in the 1996 panel. Also, total family unemployment income is called \textit{funemp} in the 1990 to 1993 SIPP panels; the variable name changes to \textit{tfunemp} beginning on page 156.

\textsuperscript{77}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 period.

\textsuperscript{78}There are 14 SIPP panels; annual, overlapping panels from 1984 to 1993, 1996, 2001, 2004 and 2008.
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.\textsuperscript{79} 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.\textsuperscript{80}

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

\textsuperscript{79}http://ceprdata.org/sipp-uniform-data-extracts/

\textsuperscript{80}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.
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 \( \{1984 \text{–} 1988, 1989 \text{–} 1993, 1994 \text{–} 1998, 1999 \text{–} 2003, 2004 \text{–} 2008, 2009 \text{–} 2011\} \). The interaction of these groups leads to 96 cells. Thus, each observation in the SIPP will be 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.\(^{81}\) 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

\(^{81}\)The person-month probability weights in the SIPP are used to calculate these averages.
after 1996.

22.3 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 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.\footnote{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).} The possible values for this variable are (i) “Not in labor force”, (ii) “Unemployed”, and (iii) “Employed”.\footnote{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.} 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 var-
able 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.

22.4 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.

22.4.a Preliminaries: Imputed Earnings

We impute earnings as follows. The \textit{incwage} variable, available for individuals in the March Supplement, 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. Next, for each year and education group (high school dropouts, high school graduates, and some college), we regress the log earnings on a set of demographic variables. The demographic variables are: 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 assigned to all CPS respondents,
regardless of their work status. This amount is inflated (or deflated) to 2010 dollars.

22.4.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\textsuperscript{84} and TRIM\textsuperscript{3}\textsuperscript{85} program rules to create an AFDC/TANF benefit calculator. For tax credits and liabilities we use the NBER’s TAXSIM\textsuperscript{9} software\textsuperscript{86}.

Micro Tax and Benefit Variables: Let \( w_{m,e,s,t,n} \) be the imputed annual earnings for individual \( m \) with education level \( e \), \( n \) number of children and living in state \( s \) in year \( t \) (the predicted values described earlier). The micro tax and benefit variables are calculated as follows:

1. We define earnings groups over a grid: \( w_{m,e,s,t,n} \in \{200, 400, 600, ..., 120000\} \), and assign individuals in the CPS to one of these groups based on their imputed earnings.\textsuperscript{87}

2. For \( \tau \in \{\text{federal taxes, state taxes, payroll taxes, AFDC, TANF, food stamps}\} \), define \( F_{\tau}(w,s,t,n) \) be the tax liability or welfare benefit for an individual with earnings \( w_{m,e,s,t,n} \), with \( n \) children, living in state \( s \) in year \( t \). We calculate \( F_{\tau} \) separately for federal, state or payroll tax liabilities, as well as AFDC, TANF and food stamp benefit levels using our welfare calculator and TAXSIM\textsuperscript{9}.

\textsuperscript{84}http://anfdata.urban.org/wrd/WRDWelcome.cfm
\textsuperscript{85}http://trim3.urban.org/
\textsuperscript{86}http://users.nber.org/\textsupersim/taxsim9/
\textsuperscript{87}Those with predicted earnings greater than $120,000 are topcoded at $120,000.

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3. After-tax income for each individual in the CPS is calculated as follows:

\[ c_{m,e,s,t,n} = w_{m,e,s,t,n} - F_{\text{Federal}}(w, s, t, n) - F_{\text{state}}(w, s, t, n) - F_{\text{Fica}}(w, s, t, n) \\
+ F_{\text{TANF/AFDC}}(w, s, t, n) + F_{\text{FoodStamps}}(w, s, t, n) \]

where \( F_{\text{TANF/AFDC}}(w, s, t, n) \) and \( F_{\text{FoodStamps}}(w, s, t, n) \) is the annual level of benefits for women with \( n \) children, income \( w \), 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. Let \( N_{e,n} \) be the number of individuals with education \( e \) and \( n \) children in our CPS sample.
2. Let \( N_{e} \) be the number of individuals with education \( e \).
3. Calculate the proportion of children in each education group

\[ \alpha_{e,n} = \frac{N_{e,n}}{N_{e}} \]

4. Calculate \( F_{r}(w, s, t, n) \) as above
5. For each state, year and education level, calculate
$$\text{MacroTax}_{s,t,c} = \sum_{n=1}^{7} F_T(w, s, t, n) \times a_{c,n}$$

6. Assign a macro tax (or after-tax income) and benefit variables to respondents in the CPS using analogous definitions as above.

22.4.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 income centile bounds. 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.

2. Next, for each education group across all years, we compute the percentage of individuals in each centile.

3. Third, 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.

4. For each year, state and number of children (0,1,...,7), we calculate
the federal, state and payroll taxes for each centile at the mean nominal level of earnings in step 3 using the NBER TAXSIM calculator. We also calculate the level of AFDC/TANF and food stamps benefits at this earnings level using the welfare calculator.

5. Finally, we are ready to construct our micro instruments. For each, year, state, education group and number of children, we aggregate the net tax and benefit liabilities from step 4 across centiles using the fixed education distribution from step 2. This leaves us with a tax variable that varies by year, state, education group and number of children.

6. For our macro instruments, we first calculate the distribution of the number of children (0,1,...,7) for each education group for all years and states. We then construct our macro instruments by aggregating the micro instruments from step 5 across family types, using the distribution of the number of children by education level.

22.5 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
• \textit{marst}: marital status of CPS respondent (7 categories); singles are either divorced, widowed or never married

• \textit{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.

• \textit{statefip}: state of residence of CPS respondent

• \textit{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)

• \textit{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 \( \text{wkswork}1 \times uhrswork \) (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 \( (\text{empstat} \geq 10 \text{ and } \text{empstat} \leq 22) \); zero otherwise (constructed variable)
• *emp.ind*: Employment status dummy variable; equal to one if respondent is employed (*empstat* ≥ 10 and *empstat* ≤ 12); zero otherwise (constructed variable)

### 23 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\(^88\) and TRIM3\(^89\), managed by the Urban Institute.

#### 23.1 Description of Welfare Program Rules

**23.1.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

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\(^{88}\)http://anfdata.urban.org/wrd/WRDWelcome.CFM

\(^{89}\)http://trim3.urban.org
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. 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.

23.1.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 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,

\footnote{90A household’s eligibility also depended on meeting asset tests set by the federal and state governments.}
provided that they help achieve four goals set forth in the PRWORA.\footnote{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.} 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.\footnote{The activities that fulfill the work requirement varies by state.} 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.

\subsection*{23.1.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

\[ FS = (MaxBen - 0.3 \times [(1 - EIDed) \times EI + OtherInc - StDed - Shelt]) \]

where \( MaxBen \) is the maximum allotment determined annually and dependent 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\(^{93}\).

### 23.2 Calculating Individual Welfare Benefits

We calculate expected annual AFDC, TANF and SNAP benefits for each woman in our CPS sample using two databases of rules. 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

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\(^{93}\)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.
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 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 12 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 sizable 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 13 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).
Table 17: Recipiency Rates of Transfer Programs

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

**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 18: OLS Regressions

<table>
<thead>
<tr>
<th>LHS Variable</th>
<th>(1) Participation</th>
<th>(2) Employment</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Micro Response</strong></td>
<td>( \frac{\partial \hat{K}<em>{i}^{\text{micro}}}{\partial T</em>{i}} )</td>
<td>( \frac{\partial \hat{H}<em>{i}^{\text{micro}}}{\partial T</em>{i}} )</td>
</tr>
<tr>
<td>Taxes Plus Benefits ( (T_{i} + b) )</td>
<td>-0.006</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td>([0.001]***)</td>
<td>([0.001]***)</td>
</tr>
<tr>
<td>Num. Obs</td>
<td>773367</td>
<td>773367</td>
</tr>
</tbody>
</table>

**Panel B: Macro Response**

<table>
<thead>
<tr>
<th>LHS Variable</th>
<th>(1) Participation</th>
<th>(2) Employment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg Taxes Plus Benefits within Labor Market</td>
<td>( \frac{\partial \hat{K}<em>{i}}{\partial T</em>{i}} )</td>
<td>( \frac{\partial \hat{H}<em>{i}}{\partial T</em>{i}} )</td>
</tr>
<tr>
<td></td>
<td>0.007</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>([0.001]***)</td>
<td>([0.001]***)</td>
</tr>
<tr>
<td>Num. Obs</td>
<td>4284</td>
<td>4284</td>
</tr>
</tbody>
</table>

Table 19: Reduced Form Regressions

<table>
<thead>
<tr>
<th>LHS Variable</th>
<th>(1) Participation</th>
<th>(2) Employment</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Micro Response</strong></td>
<td>( \frac{\partial \hat{K}<em>{i}^{\text{micro}}}{\partial T</em>{i}} )</td>
<td>( \frac{\partial \hat{H}<em>{i}^{\text{micro}}}{\partial T</em>{i}} )</td>
</tr>
<tr>
<td>Taxes Plus Benefit with takeup: sim</td>
<td>-0.055</td>
<td>-0.052</td>
</tr>
<tr>
<td></td>
<td>([0.003]***)</td>
<td>([0.003]***)</td>
</tr>
<tr>
<td>Num. Obs</td>
<td>773367</td>
<td>773367</td>
</tr>
</tbody>
</table>

**Panel B: Macro Response**

<table>
<thead>
<tr>
<th>LHS Variable</th>
<th>(1) Participation</th>
<th>(2) Employment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg Taxes Plus Benefit with takeup: sim</td>
<td>( \frac{\partial \hat{K}<em>{i}}{\partial T</em>{i}} )</td>
<td>( \frac{\partial \hat{H}<em>{i}}{\partial T</em>{i}} )</td>
</tr>
<tr>
<td></td>
<td>-0.027</td>
<td>-0.025</td>
</tr>
<tr>
<td></td>
<td>([0.014]*)</td>
<td>([0.015])</td>
</tr>
<tr>
<td>Num. Obs</td>
<td>4284</td>
<td>4284</td>
</tr>
</tbody>
</table>
Figure 12: Budget Set Components

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 food stamps. 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 13: Example Budget Sets for Selected States and Years

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 14: Optimal Tax and Transfer Schedule Comparing KKLS Formula with Saez (2002) Formula, Redistribution parameter \( v = 1 \)

Notes: The figure corresponds to Figure 2 in the main paper, but with the parameter measuring preferences for redistribution \( v \) 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 15: 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 $\nu$ 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 16: Optimal Tax and Transfer Schedule in Weak vs. Strong Labor Markets, Redistribution parameter $\nu = 1$

Notes: The figure corresponds to Figure 4 in the main paper, but with the parameter measuring preferences for redistribution $\nu$ 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.
References


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