How Does Unemployment Affect the Desirability of the EITC vs. NIT? Theory and Evidence *

PRELIMINARY DRAFT - PLEASE DO NOT CITE

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Abstract

Recent decades have witnessed a large shift in the U.S. tax and transfer system away from unconditional transfers to aid the poor towards making transfers and tax credits conditional on working. In particular, for single mothers, incentives to work increased dramatically through the Welfare reform in 1997 and the stepwise expansion of the Earned Income Tax Credits (EITC). In this research project we investigate whether the shift towards making transfers conditional on working comes with costs during deep recessions, such as the Great Recession, when labor markets are particularly bad. In such an environment, the targeted population may be unable to find jobs at all and thus rather than moving people from non-employment to employment, making benefits conditional on working only leads to large cuts in transfers to the affected (very poor) population. To analyze this we use data from the CPS and state-year level variation in taxes and transfers to measure how labor supply elasticities vary with the economic environment and show how these estimates can be used to determine how the design of the optimal tax and transfer system depends on labor market conditions. We interpret our findings within a model of optimal taxes and transfers and find potentially large welfare gains from moving to a system where unconditional transfers to the poor and work incentives vary over the business cycle, similar to unemployment insurance extensions in the US.

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1 Introduction

The two decades between the mid-1980s and early 2000s witnessed a large shift in the U.S. tax and transfer system away from unconditional transfers to aid the poor towards making transfers and tax credits conditional on working. In particular, for single mothers, incentives to work increased dramatically: welfare benefits were cut and time limits introduced, the Earned Income Tax Credit (EITC) was expanded, and changes in Medicaid, training programs and child care provision encouraged work. The literature evaluating these policy changes largely views them as successful. These reforms sharply reduced welfare caseloads and increased labor force participation of single mothers (e.g. Eissa and Liebman 1996, Meyer and Rosenbaum 2001, and Eissa and Hoynes 2006) and slightly increased consumption levels (Meyer and Sullivan 2004, 2008).

There are theoretical arguments for why governments should favor the use of conditional transfers over unconditional transfers. First, Saez (2002) extends the Mirrlees (1971) and Diamond (1980) framework to show that when labor supply responses are concentrated along the extensive margin relative to the intensive margin - as the empirical evidence indicates - optimal income transfers take the form of an Earned Income Tax Credit, as opposed to a Negative Income Tax. Such a system, characterized by negative marginal tax rates at the bottom of the income distribution, may be optimal since it encourages people into the labor force without encouraging higher wage earners to reduce their hours of work. Second, research by Eissa, Kleven and Kreiner (2008) has shown that the tax policy reforms substantially improved welfare. Given the accumulating evidence on the effectiveness of conditional transfers, several governments around the world, for instance, Canada, Norway, Sweden and the UK, are reforming their welfare systems by moving towards in-work tax subsidies.

It is important to note however, that the policy evaluations all took place during the 1990s and early 2000s when the U.S. economy was performing quite well and unemployment rates were declining dramatically or at least remained at historically relatively low levels (even the peak of the 2003 recession had unemployment at only 6.3 percent). Since 2008, the economic environment has changed dramatically with unemployment rising above 10 percent and remaining high for a prolonged period of time. This raises a potential concern: Increasing the returns to work, by making transfers and tax credits conditional on working, may be an effective tool to increase labor force participation when it is relatively easy for single mothers to enter the labor force and find jobs. However, when labor demand is slack, some individuals will remain jobless, despite the fact that they search for a job at the market wage. In this case, making transfers conditional on working may not lead to increased employment, but instead may sharply reduce consumption and wellbeing of the targeted population. As such, it may in fact be preferable to have the design of transfers to the poor depend on the state of the business cycle, with less work requirements during economic downturns and more work incentives during upswings.

The key question that we consider in this paper is: how does the presence of unemployment affect the desirability of the EITC compared to the NIT? To cast light on this question, we consider a job search model that nests Saez (2002). In our model, individuals can be out of work by choice ("non-participants") or by failing in their search to find a job ("unemployed"). This relaxes the incentive constraint the government faces since transfers to the unemployed can be raised without adversely affecting job search behavior. Infact, increasing transfers to the unemployed can raise labor force participation since the penalty of not finding work is lessened. In Saez (2002), labor demand is perfectly elastic and the employment responses to taxation are governed entirely by labor supply. We depart from Saez by allowing labor demand to endogenously depend on taxes. This could arise, for example, in a search-and-matching model with ex-poste wage bargaining or in a "rat race" model with a fixed number of jobs. Thus, our model is general equilibrium. For the version of our model that considers the extensive margin only, we show that the optimal participation tax is the same as the one obtained by Saez, except for a new term which represents an externality that depends on the wedge between the micro and macro extensive margin elasticities.

Our welfare formula are derived in terms of estimable policy parameters. Therefore our model is in the spririt of the "sufficient statistics" approach to welfare analysis (Chetty 2009). The second contribution of this paper is to estimate the reduced-form parameters that are inputs to the optimal tax formula. Using data from the Current Population Survey (CPS) and state-year level variation in welfare policies (AFDC, TANF and SNAP), as well as state and federal income taxes (including the EITC) for over 20 years, we estimate how the labor supply effects of these programs vary with state unemployment rates.[1] The implied labor supply elasticities can then be used to calculate how the tax and transfer reforms have affected overall welfare during the 2008 and 2009 recession. Our baseline specification indicates that the participation elasticity with respect to the average net-of-tax share is 0.2 and is statistically significant. This is in line with other estimates in the literature (Eissa, Kleven and Kreiner 2008). We also find that the elasticity is 0.27 for a two standard deviation increase in our measure of state unemployment and is 0.14 for a two standard deviation decrease in state unemployment.

This paper is closely related to recent research on whether the generosity of Unemployment Insurance (UI) benefits should vary over the business cycle. 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 unemployment insurance (UI) is inversely related to the labor supply elasticities. Schmieder, von Wachter and Bender (2012), Landais, Michaillat and Saez (2010), Kroft and Notowidigdo (2011) 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 evidence that the labor supply elasticities determining the optimal

[1] In ongoing work, we are collecting data on Medicaid, time limits, work requirements, child care and job trainings programs that expanded during the 1990s.

benefit durations (Schmieder et al.) and levels (Landais et al. and Kroft and Notowidigdo) decline during recessions and that the generosity of the UI system should therefore increase during a recession.

More broadly, our paper relates to an active empirical literature exploiting variation in labor market conditions to inform theories of the labor market. For example, Davis and von Wachter (2011) find that the cost of job loss is higher during recessions and argue that this is inconsistent with a standard Mortensen and Pissarides (1994) model of the labor market. Another example is the Crépon et al. (2013) experimental study of job placement assistance, which finds that the negative spillover effects of the experiment (i.e., crowd-out onto untreated individuals) are larger when the labor market is slack. They interpret this evidence as consistent with a model of job rationing (Landais, Michaillat, and Saez 2013). A more direct test of spillovers created by UI benefits is provided by Lalive, Landais and Zweimuller (2013) who show that the unemployment spells of UI ineligibles were affected by a large expansion of Austria's UI benefits.

There are also papers that directly examine how labor supply responses to taxation vary with local labor market conditions. 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. We build on these papers by developing a theoretical framework and using this framework to guide our empirical and welfare analysis.

Our work also builds on the recent literature of optimal taxation models that incorporate involuntary unemployment (Hungerbühler, Lehmann, Parmentier, Van der Linden 2006, Hungerbühler and Lehmann 2009, Jacquet, Lehmann and Van der Linden 2011, Lehmann, Parmentier and Van der Linden 2011).[2] These papers build on Saez (2002) by incorporating search frictions. There are several differences between our paper and these papers. First,

[2]See Boadway and Tremblay (2012) for an excellent review of this literature.

their theory only consider extensive margin responses but mention that future work should incorporate intensive margin responses. Our model incorporates the intensive margin. Second, they place alot of structure on the model. For example, they assume a matching function with constant return to scale and Nash bargaining where the bargaining weights are chosen to satisfy the "Hosios condition" (Hosios 1990). Our approach is more reduced-form in that it nests many different structures of the labor market, as in Landais, Michaillat and Saez (2010). Finally, they do not connect their key formula to the micro and macro elasticities. We highlight the roles of these elasticities in the welfare formula and estimate them.

We also add to the large literature evaluating the impact of the EITC exansions in the 1980s and 1990s by expanding the analysis horizon until the most recent years. 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 (2001) exploit variation in the EITC up until 1996, controlling for changes to welfare (AFDC and food stamps), Medicaid, Child Care, and jobs training during this time period. 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 supply of single women and their allocation of time to market work versus home production. All of these papers rely on the fact that the EITC reforms impacted single women with children, but not single women without children.

Finally, our work broadly relates to research which permit demand-side variables to determine employment outcomes for males and females. Blundell, Ham and Meghir (1987) shows that demand charactistics, 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 rest of the paper proceeds as follows. Section 2 develops our theoretical model.

Section 3 contains details on Institutional background and describes our data. Section 4 contains our empirical results. Section 5 considers the policy implications of our theoretical and empirical findings. The last section concludes.

2 Theoretical Framework

Saez (2002) shows that the optimal tax and transfer schedule, especially towards the lower end of the income distribution, depends critically on the relative magnitudes of two elasticities: the extensive margin labor supply elasticity, or the propensity to leave or enter the workforce in response to potential income changes, and the intensive margin labor supply elasticity, the propensity to adjust the number of hours worked in response to changes in the marginal tax rate implied by the tax schedule. A sizable unconditional transfer phased out with high marginal tax rates is optimal when the intensive elasticity is large and the extensive elasticity is small. The high phase out rates limits the number of individuals exposed to the incentive to reduce hours worked provided by the high marginal tax rate. When the extensive elasticity is high and the intensive is low, it can be optimal to provide extra incentives to work by offering a negative marginal tax rate for low incomes. This corresponds to the basic features of the Earned Income Tax Credit (EITC) in the US.

The critical assumption underlying Saez's framework is that labor demand is perfectly elastic. In this case, all unemployment is voluntary and there are no spill-over effects between workers, i.e. one worker working more does not decrease the probability of finding a job for other workers. Our frameworks permits the possibility that an individual searches for work, but is unable to find it and that there are externalities, since workers are competing for the same jobs thus potentially crowding each other out.

2.1 Model Set Up

Our model builds on the Saez (2002) framework, but extends it by explicitely allowing for involuntary unemployment and general equilibrium effects. While we develop a model that allows for labor supply responses on the intensive and the extensive margin, we focus here on presenting a restricted version of the model that only contains extensive margin labor supply responses. This allows for a more concise and intuitive exposition and we leave the development of the full model (the 'mixed' model in Saez's language) for the appendix and only briefly point out it's implications.

The labor force in the economy consists of individuals indexed by $m \in M$ being a (possibly multi-dimensional) set of measure one. The measure of individuals on M is denoted by $dv(m)$. There is a discrete and finite number of possible occupations an individual can choose to work in. Individuals chose in which occupation to look for work and whether they are looking for work at all. The labor supply decision of individual m is denoted by $i^* \in \{0, 1, ..., I\}$, where $i = 0$ represents choosing not to work. We depart from Saez by incorporating "search frictions". Specifically, we assume that workers who join the labor force search for a job in occupation i and are successful with probability l_i, which may vary by occupation. If an individual does not find a job, then the person is unemployed and this status will be indexed as $i = -1$.[3] Thus, unlike in Saez (2002), unemployment and non-participation are distinct labor market states.

Occupations are ranked according to the wage, so that $w_{i+1} > w_i$ for all $i > 0$. Furthermore, $w_{-1} = w_0 = 0$; that is, the unemployed and the people not in the labor force have no labor income. There is a tax and transfer system in place, which is summarized by a function $T(w_i) = T_i$, such that $c_i = w_i - T_i$ is the net-of-tax income in occupation i. We allow for negative T_i which would then represent a transfer to indivdiuals in occupation i. Individual $m \in M$ has a utility function of $u^m(c_i, i)$ defined on after-tax income $c_i \geq 0$ and job choice i. Each individual chooses i to maximize $u^m(c_i, i)$.

Thus individuals can respond to changes in the tax and transfer system on the extensive margin, choosing between $i = 0$ and $i > 0$ and on the intensive margin, choosing a higher

[3]Since we consider a static model, we implicitly treat unemployed workers as if they are permanently unemployed. Thus, the optimal tax policy serves as a redistribution tool, rather than an insurance tool. See Boadway and Tremblay (2012) for a discussion of this.

i. We focus on the special case where labor supply responses are concentrated along the extensive margin margin, and leave the development of a model with extensive and intensive margin responses to the appendix.

Let the fraction of workers who search for a job in occupation i be $k_i(c_{-1}, c_0, ..., c_I)$. For now, we do not allow k_i to depend on l_i.[4] The total number of people actually working in occupation i is given by $h_i = l_i k_i$. The number of people not in the labor force is $h_0 = k_0 = 1 - \sum_{i=1}^{I} k_i$ and the number of people unemployed is: $h_{-1} = \sum_{i=1}^{I}(1-l_i)k_i = 1 - k_0 - \sum_{i=1}^{I} l_i k_i$.

Social Planner

We can partition the set M into two subsets defining the sets of individuals that are in the labor force and not in the labor force, M_L and M_L, respectively. The social planner chooses to $(T_{-1}, T_0, ..., T_I)$ to maximize social welfare given by:

$$W = \int_{M_L} \mu^m \left(l_{i^*} u^m(w_{i^*} - T_{i^*}, i^*) + (1 - l_{i^*}) u^m(-T_{-1}, -1) \right) dv(m) + \int_{M_N} \mu^m u^m(-T_0, 0) dv(m)$$

where μ^m are positive weights and subject to the budget constraint $\sum_{i=-1}^{I} h_i T_i = E$. Let p denote the multipler of the budget constraint.

Similarly as in Saez, define the marginal social welfare weight for occupation i:

$$g_i = \frac{1}{p h_i} \int_{M_i} \mu^m l_{i^*} \frac{\partial u^m(c_{i^*}, i^*)}{\partial c_i} dv(m)$$

As in Saez, the sum of g_i over all i equals one [check this]. Using this definition, the first-order condition for tax T_i can be rewritten as:

$$(1 - g_i) h_i - \frac{1}{p} \sum_{j=1}^{I} \frac{\partial l_{j^*}}{\partial c_i} \Delta u^m_{j^*} k_{j^*} = \sum_{j=-1}^{I} \frac{d h_j}{d c_i} T_j \qquad (1)$$

[4] The decision of workers to go into occupation i can be expressed as a function of the probability of finding a job there $k_i = k_i(l_i)$. The term $\eta_i = \frac{\partial k_i}{\partial l_i} \frac{l_i}{k_i}$ is the **discouraged worker elasticity** in Landais, Michaillat and Saez (2012).

where $\triangle u_{j^*}^m = \frac{1}{k_j}\int_{M_j} \mu^m \left(u^m(c_{j^*}, j^*) - u^m(c_{-1}, -1)\right) dv(m)$ is the utility loss of an invididual who would like to work in occupation i but who is pushed into involuntary unemployment by the tax change. Intuitively a tax change on occupatio i has three components, highlighted by the terms in equation (1): it increases the welfare of h_i individuals by the marginal social welfare weight for that occupation (first term), it may change job finding probabilities in other occupations (second term), and it may lead to tax losses, which are valued at the value of the lagrange multiplier p (the last term).

2.2 Extensive Margin Model

The model in the previous part is very general, but also not very tractable in its fully flexible form. We now analyze a version of this model under some addtional simplifying assumptions that restrict possible labor supply responses to the extensive margin. We are currently working on extending the model to allow for intensive margin repsonses.

Assume individuals can only choose between $i = 0$ and the one corresponding to their own skill level. This implies that the function h_i depends only on c_{-1}, c_0 and c_i for $i > 0$.

Following Landais, Michaillat, and Saez, we assume that the conditional job-finding rate l_i is a function of the utility gain from work. The equilibrium job-finding rate will be pinned down by the model of the labor market. We have that: $h_i = l_i k_i(\Delta c_i)$. Define the extensive margin micro labor supply elasticity:

$$\epsilon_i^m = \frac{\Delta c_i}{h_i}\frac{\partial h_i}{\partial \Delta c_i} = \frac{\partial k_i}{\partial (c_i - c_0)}\frac{c_i - c_0}{k_i}$$

The extensive margin macro labor supply elasticity is:

$$\begin{aligned}
\epsilon_i^M &= \frac{\Delta c_i}{h_i}\frac{dh_i}{d\Delta c_i} \\
&= \frac{\Delta c_i}{h_i}\left(\frac{\partial k_i}{\partial \Delta c_i} l_i + \frac{\partial l_i}{\partial \Delta c_i} k_i\right) \\
&= \epsilon_i^m + \frac{\Delta c_i}{l_i}\frac{\partial l_i}{\partial \Delta c_i}
\end{aligned}$$

$$= \quad \epsilon_i^m + \varepsilon_i$$

We can define the job-finding rate elasticity (the effect of increasing work incentives in occupation i on the job finding rate in occupation i):

$$\varepsilon_i = \frac{\partial l_i}{\partial \Delta c_i} \frac{c_i - c_1}{l_i}$$

Suppose we assume that $T_0 = T_{-1}$, i.e. UI benefits are the same as basic income (e.g., because the government can't condition on whether individuals are actually looking for a job).

In the appendix we show that the first order condition, equation (1), can be expressed as:

$$\frac{T_i - T_0}{c_i - c_0} = \frac{(1 - g_i)}{\epsilon_i^M} + \frac{1}{p} \frac{\Delta u_{i^*}^m}{\Delta c_i} \left(\frac{\epsilon_i^m}{\epsilon_i^M} - 1 \right) \tag{2}$$

The left-hand side is the participation tax, the percentage of income that an individual loses if he decides to participate in the labor force. The right hand side depends on the standard term in Saez and a new term. The numerator of the first term is an equity effect. It represents the marginal social value of transferring \$1 from a type i worker to the government. The denominator is an efficiency effect and represents the effect of increasing the participation tax on a type i individual. Assuming that $\epsilon_i^m = \epsilon_i^M$, if for low values of i, $g_i > 1$, a negative participation tax on low-skilled workers is optimal. Now consider the second term. It is proportional to the ratio of the micro to macro elasticity. If the micro elasticity is less than the macro elasticity, this term is negative and this pushes us in the direction of a negative participation tax.

3 Data

3.1 Current Population Survey

The bulk of data we use come from the CPS. Both the monthly outgoing rotation group data (ORG) and the March annual data are included. We currently use data from 1984-2011, ORG data from IPUMS spans in 1994-2010 so when we extend the data back to 1984 and include 2011 we will only be adding data from the March CPS. We merge the CPS individual level data with various aggregate data.

In our empirical analysis below, we define "employment" as a dummy variable that takes on a value of 1 if the CPS respondant claimed thier employment status was either "At work" or "Has job, not at work last week". For details on the data construction see Appendix A.

3.2 Description of Welfare and Tax Calculator

We calculate federal and state tax liabilities (or subsidies) using the NBER's TAXSIM software. TAXSIM takes as inputs severeal earnings, expenditure and demograpic required to calculate and individual's tax liability. For the purposes of our analysis we supply TAXSIM with the state the individual is living in, the year of record, marital status (in our case this is always single), number of children and wage earnings. After passing these variables, TAXSIM returns separately federal, state and FICA liabilities. For reasons described above, we do not pass TAXSIM the individual's actual reported wage earnings to TAXSIM. Instead we pass a hypothetical potential wage. In most cases this is $15,000 adjusted for inflation. We aslo calculate any tax credits the indiviual might be eligible for if they do not work by passing zero income along with all of the other relevant variables to TAXSIM.

To caluclate welfare benefits we construct a benefit calculator based on rules published in the Welfare Rules Database, managed by the Urban Institute. In general, welfare benefits are phased out as an individual earns income. In most cases a welfare recipiant is allowed an earned income disregard: a small amount of income one can earn while maintaining eligibility for maximum welfare benefits. There is often a maximium amount of monthly income an individual can earn before they are altogether disqualified for welfare benefits. If an individual earns more than the disregard but less than the maxium earnings in a month, then each additional dollar of earning reduces benefits by a constant amount. Prior to 1996 the federal governemnt set standard rules for both the income disregard, at $120 per month, and the phase out rate of 33 percent. Furhtermore, prior to 1996, there were no time limits on the duration an individual could collect welfare benefits. With a few exceptions, all states followed these rules, but were able to choose benefit levels dependant on the number of children in the household. After 1996, states were granted more felxibility to choose both the phase out rate and the earned income disregard as well as time limitations and work requirements. Since our sample at most observes a household over a 16 months, we cannot calculate how many years an single mother would have been eligble for these benefits. So in our analysis we assume that the individual has not exhausted thier welfare eligibility. Our calcluator takes as inputs, state or residence, year of record, number of children and income and reports the welfare beneifts an for which individual would be eligible.

To calucluate the average effective tax rate at a given earnings level, we combine the output from TAXSIM and our welfare benefit caluclator. Let pre-tax income be given by z, taxes be given by $T(z)$ and transfers be given by $B(z)$. Let post-tax and transfer income be given by $y = z - T(z) + B(z)$. The average effective tax rate at z is defined as $ATR(z) = \frac{T(z)+B(0)-B(z)}{z}$. First, for each individual we cacluate their income if they had zero earnings, the bulk of this income comes from welfare benfits, but some child credits in the tax code may also add to this. Then we calculate income if the individual earned a hypthetical amout, most often in our analysis this is $15,000 adjusted for inflation. From the income levels at zero and $15,000, we can calculate the average effecitve tax rate as $ATR(15k) = \frac{Income\ at\ \$15k - Income\ at\ \$0}{\$15{,}000}$.

The shift to TANF also 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. In order to be able to link our empirical analysis directly to the theory, we make the simplifying assumption for much of our main analysis, that all potential TANF recipients, i.e. eligible based on income, children and marital status, would in fact receive TANF. We are currently working on alternative ways to deal with incomplete take-up and eligibility due to these requirements.

Figure 1 shows that variation in our time period coming from the EITC reforms, by simply showing the maximum EITC level a single individual could receive depending on the number of chilren they have. 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 also expanded for parents with 3 children. The figure clearly shows that there is substantial variation across time and across number of children. Much of the literature has focused on evaluating the two large expansions in 86 and in the 1990s, but it is important to realize that for our goal of estimating how labor supply elasticities *change* over the business cycle, it is also possible to use the simply across children variation after the 1990s reforms. In our empirical results we present a plethora of robustness checks showing that our main result holds for many different controls, isolating different parts of the available variation for identification.

In Figure 2 we show how the net of tax rate, $1 - ATR$, which would be responsible for extensive margin labor supply decisions (for an individual with \$15,000 income) changed over the last 25 years. The net of tax rate here is computed using the definition of ATR from above, that is taking into account AFDC or TANF benefits as well as taxes. Figure 2 (a) shows that the returns to working have changed dramatically for a single parent, while staying virtually unchanged for a single without children. In 1985 the net of tax rate was as low as 40%, implying that an individual making 15,000 per year was facing an effective average tax rate of 60%. At the end of our period this has changed dramatically with a single mother with 2 children facing a net of tax rate in 2011 as high as 115%, or an effective negative tax of -15%. This dramatic increase in work incentives has been accompanied by a dramatic fall in benefits levels at zero income. In 1984 a single mother of 2 children could expect between $9000 of welfare payments if she was not working, which fell to $6000 in 2011 - a cut in benefits of 50% in real terms.

3.3 Other Variables

Monthly state unemployment data come from the Federal Reserve Economic Data (FRED). These data are current vintage, seasonally adjusted. National inflation rates come from FRED CPI figures series Consumer Price Index for All Urban Consumers: All Items (CPIAUCSL).

Table 1 contains our summary statistics for our sample of single women. We see that the average age is around 35 years. Roughly 30 percent of households have a child under the age of 18 years and about 10 percent have a child under the age of 5 years. The average number of years of education is 13. Additionally, 13 percent of households are high school dropouts, 32 percent are high school graduates, and the remaining 55 percent have either some college or are college graduates. Roughly 19 percent of women are black and 12 percent are hispanic. Finally, 39 percent live in a central city; this variable is created from the categorical variable "Metropolitan cetnral city status" and equals one if the respondant describes thier location as "central city". The average net-of-tax share is 80 percent, the average maximum EITC benefit is $1480, the average maximum annual TANF/AFDC benefit is $1432 [this appears low because women w/out children all recieve zero], and the employment rate is 75 percent.

Columns (2) and (3) report means for the sub-samples with low and high unemployment, respectively. Looking across columns (2) and (3), we see that when unemployment is low, women are less likely to be observed with children under 18 years, are slightly less likely to be black or hispanic, are less likely to live in a central city, have higher maximum EITC and TANF/AFDC benefits, and are more likely to be employed.

4 Empirical Analysis

We begin our analysis by examining non-parametrically the impact of taxes and transfers on labor supply and how this effect varies with local labor market conditions. To quanitfy the magnitude of these effects and to conduct a series of robustness tests, we next turn to regression models.

4.1 Graphical Analysis

We use the variation in Figure 2 to investigate the relationship between taxes and labor supply. Figure 3 provides non-parametric evidence on the effects of the average net-of-tax share at $15,000 on the employment rate. To create this figure, we regression adjust the data using state, calendar year-month and number of children fixed effects. Given our set of fixed effects, we are identifying labor supply responses using tax rate variation within state and number of children groups, over time. We then split the data into discrete average effective tax rate bins of size 0.02 and compute the average adjusted employment probability. The fitted line overlayed on the scatterplot represents the fitted line corresponding to the following regression:

$$P(Employed_{icst}) = \alpha + \beta \cdot (1 - ATR_{icst}) + \delta_s + \delta_t + \delta_c + \varepsilon_{ist} \tag{3}$$

where i indexes individual, c indexes number of children (age restriction?), s indexes state, t indexes calendar year-month. The evidence in this figure suggests that labor supply is strongly increasing in the average net-of-tax share.

Our next figure investigates whether the labor supply effects of taxes and transfers vary with labor market conditions. In Figure 3, we report the same data as in Figure 2, but we do for the sub-samples where the unemployment rate in a given state and year-month is high (state unemployed above 9 percent) and low (state unemployment below 9 percent) or falling (lower compared with 6 months prior) unemployment rates respectively. The relationship between the employment probability and the net-of-tax-rate is clearly stronger and steeper when the unemployment rate is fallin. The evidence from these figures suggest that employment incentives of the tax and transfer system are significantly more effective when labor markets are performing strongly, and the succeed much less well in pulling people into employment when labor markets are weak.

4.2 Regression Results

The visual plots provide compelling evidence that the labor supply responses to taxation vary over the business cycle. We next turn to regression models to quantify the magnitude of these effects. We estimate the following equation which allows labor supply responses to vary with local labor market conditions:

$$\begin{aligned} P(Employed_{icst}) &= \alpha + \beta \cdot (1 - ATR_{icst}) + \gamma \cdot u_{s,t} + \lambda \cdot (1 - ATR_{icst}) \times u_{st} \\ &\quad + \delta_s + \delta_t + \delta_c + \eta \cdot X_{icst} + \varepsilon_{icst} \end{aligned} \tag{4}$$

where $1 - ATR_{icst}$ is the average net-of-tax share which varies at the individual level with among other things, the number of children (c), the state of individual (s), and the calendar year (t), $u_{s,t}$ is a measure of unemployment in state s at time t, δ_s is a state fixed effect, δ_t is a calendar time fixed effect, δ_c is a number of children fixed effect, and X_{icst} is a vector a set of demographic control variables (age, years of education, and dummies for educational attainment, hispanic ethnicity, non-white race, and urban residency). The parameter λ tells us how labor supply responses vary with local labor market conditions. For our baseline specification, we use the past 12 month change in the state unemployment rate as a measure of unemployment. Below we also report results using alternative measures of unemployment.

The identifying assumption that allows us to interpret λ as a test of whether labor supply responses vary with unemployment is the following: conditional on the average net-of-tax share, state fixed effects, year fixed effects, number of children fixed effects and control variables, there are no omitted determinants of employment that vary with the interaction of state unemployment and the average net-of-tax share. We evaluate this assumption below by controlling flexibly for local labor market conditions.

One threat to identification concerns migration responses to state welfare policies. According to McKinnish (2005), single mothers on welfare are a relative immobile group and thus, any migrants account for a very small share of a state's welfare caseload. This view is further buttressed by Gelbach (2004) who argues that welfare migration is unlikely to create endogeneity bias in regressions that rely on cross-state variation in welfare policies.

4.2.1 Baseline Results: Effects of Tax and Transfers on Labor Supply

The first row in column (1) of Table 2 shows that $\hat{\beta} = 0.19$ implying that a 1 percentage point increase in the net-of-tax share leads to a .19 percentage point increase in the probability of employment. This effect is statistically significant at the 1% level. The implied elasticity with respect to the net-of-tax share is 0.21. This elasticity estimate is slightly below existing estimates from the literature. In columns (2) and (3), we report results for a subset of the sample with low ($\leq$ 12 years) and high ($\geq$ 16 years) education, respectively. Since many of the large reforms to the tax and transfer system, such as the expansion of the EITC in the 1990s, affected primarily low-skilled mothers, we would expect to see a much larger effect for the low education group. This is what we find. Column (2) reports an elasticity of 0.32 for the low education group and column (3) reports an elasticity of 0.04 for the high education group. This lends support to a causal interpretation of our estimates.

4.2.2 Labor Supply Responses by Labor Market Conditions

The next row in Table 2 reports the coefficient on the interaction between the average net-of-tax share and the past 12-month change in the state unemployment rate. Consistent with the evidence in Figure 4, we find that $\hat{\lambda} = -0.03$ and is statistically significant at the 1%

level. Our results imply an elasticity of 0.14 for a 2 standard deviation increase in the 12-month change in the unemployment rate and an elasticity of 0.27 for a 2 standard deviation decrease in the 12-month change in the unemployment rate.[5]

Table 5 report results using different measures of $u_{s,t}$ in equation (5). The first row reproduces our baseline estimates for comparison. The second row uses the past 6-month change in the unemployment rate. We see the results are identical to using the past 12-month change. The next two rows interact the average net-of-tax share with the level state unemployment rate and the log unemployment rate, respectively. Our interaction effect is statistically insignificant in both specifications. In rows 5 and 6, we define a threshold rule using whether the state unemployment rate exceeds the median unemployment rate in a given year (row 5) and 9 percent (row 6). The interaction effect is statistically insignificant in row 5 but is significant in row 6, showing that the marginal effect is half the size in magnitude when the unemployment rate exceeds 9 percent. In rows 7 and 8, we consider the effect during a recession, defined as an NBER recession year, and during the Great Recession (2008-2010). We see in both specifications that the elasticity is significantly lower in both cases. Finally, in the last row, we define the net-of-tax share using only taxes and interact this variable with the log state unemployment rate. Our results are consistent with our baseline specification. Taken together, our empirical results suggest that the participation elasticity is significantly lower during recessions.

Figure 5 explores these relationships a bit more by estimating our baseline specification separately for different states of the labor market, in particular by 0.5 percentage point bins in the unemployment growth rate over the last 6 months. The figure shows the implied labor supply elasticities for the different levels of the unemployment growth rates. While in times of falling or stable unemployment rate there is a substantial labor supply elasticity, this becomes much weaker during economic downturns and fast growing unemployment.

[5]The mean change is -0.1 so 1 standard deviation above the mean is 1.2 percentage points and 1 standard deviation below the mean is 1.3 percentage points.

4.2.3 Micro vs. Macro Effects

Our theoretial framework highlights the importance of distinguishing micro- from macro elasticities. If there are substantial labor market spillovers between recipients of the EITC / welfare benefits and non-recipients, then the labor supply elasticities typically estimated in applied micro studies may significantly overstate the disincentive effects of high marginal tax rates, since the increased job search efforts by one group, simply reduce the job finding probability (and potentially decision to search for jobs at all) of another group of workers. Estimating micro- and macro elasticities separately is a difficult task and few studies have done so convincingly (e.g. Lalive, Landais, Zweimueller 2013, or Crepon, Duflo and Gurgand 2013).

Our estimates above likely identify a mix between a micro and a macro elasticity. Since our implicit comparison groups are both workers in other states and years, as well as women with different numbers of children within the same year-state cell, we expect that our elasticities would capture some spill-over effects and be located somewhere between the true micro and macro elasticity.

We provide some evidence on that micro and macro elasticity in Table 7. To obtain an estimate as close as possible to a micro elasticity, column (1) estimates our baseline specification, without the UR interaction term, but controlling fully for State X Year X Month fixed effects. Thus all comparisons occurr within single month - state cells, capturing how women with higher net of tax rates fare compared to women with lower net of tax rates within the same labor market. Column (2) goes the other extreme, completel ignoring within state-year cell variation, and instead collapsing the data to the state-year-month cell level, assigning each cell the average net of tax rate within the sample population. We then regress the fraction of individuals employed on the net of tax rates. The point estimate is only about half the size of the estimate in column 1 and not statistically significant (though it would be on th 10% level).

Column (3) follows the specification in Crepon et al (2013) and regresses individual employment on the net of tax rate of that individual as well as the average net of tax rate within the state-year cell. The effect of the net of tax rate is the same as in column (1), but the average net of tax rate is clearly significantly negative and off the same size. This means that an individual in a labor market where other workers face very high work incentives would have a much lower probability to be employed, again suggesting substantial spill-over effects.

4.2.4 Robustness Checks

Finally, we undertake a sensitivity analysis to investigate the robustness of our results. In column (2) of Table 3, we include a variable that represents the income transfer if the mother is not working, as well as the interaction between this variable and state unemployment. Our estimates are robust to the inclusion of this variable. We also find, as expected, that transfers when not working have a negative effect on employment with the results suggesting that this impact is attenuated when unemployment is high. The last column of Table 3 calculates the average net-of-tax share using only taxes and includes a variable representing the average net-of-tax share using only welfare payments (e.g., AFDC/TANF). This specification follows Gelber and Mitchell (2012). We find a slightly larger effect on the coefficient for the net-of-tax share using taxes only than we do on the net-of-tax share defined using transfers. The interaction of these variables with our unemployment measure is similar in magnitude to our baseline specification and is statistically significant.

In Table 4, we control flexibly for observable and unobservable trends. Columns (1) through (6) control flexibly for local labor market conditions by including polynomials of $u_{s,t}$ that increase in order (columns (1) - (4)). In columns (5) to (7), we interact state unemployment with state fixed effects (column (5)), year fixed effects (column (6)) and both state and year fixed effects (column (7)). These specifications capture the possibility that in certain states or years, the tax and transfer system may be unusually responsive to local labor market conditions. In column (8), we control for state-specific time trends. Finally, in column (9), we include an interaction between the average net-of-tax share and year fixed effects. If taxes and transfers respond to observable and unobservable national labor market conditions, then including year fixed effects addresses the problem. The concern is that when the national labor market is bad, taxes and transfers are more correlated with labor market conditions than when national labor market is good. In this case, are estimates will be biased. One strategy for dealing with this is interacting year fixed effects with the net-of-tax share and including this as a control. This means that any variation in taxes and transfers that is correlated with the (unobservables in the) year fixed effects is not variation we use to identify the interaction term. Reassuringly, our results are fairly robust across all of these specifications.

Our final robustness check tests whether there is selection on observables. If the marginal individual varies with local labor market conditions in a way that makes them more responsive to taxes and transfers, then our estimates could be picking up a selection effect. In Table 5, we include interactions between the average net-of-tax share and observable characteristics of workers alongside our interaction effect of interest. Our main estimates remain very stable across the columns of the table suggesting selection is not what is driving our results. Of course, we cannot rule out selection on unobservables.

5 Simulations

The analysis so far has shown clearly that the labor supply effects of the EITC and welfare benefits vary over the business cycle and become much stronger during strong labor market. During downturns individuals, voluntarily or not, respond much less to strong financial work incentives, thus indicating that a transfer system that only provides income support to working individuals, may not be sucessful in pushing people into the labor force in recessions.

We use our theoretical framework in order to solve for the optimal tax and transfer system under different calibrations for the extensive margin labor supply elasticity. Using otherwise the same calibration as Saez (2002), we solve the optimal transfer system under the assumption that the labor supply elasticity is 0.4 or 0.1. Figure 6 shows these simulated budget sets for the two regimes assuming a zero wedge between micro and macro elasticities. Clearly the shape of the optimal budget set more closely resembles the current TANF / EITC system, when the economy is doing very well.

Figure 6 (b) shows the same results for a quite low elasticity of 0.1, showing that in this case the optimal transfer system much more resembles a negative income tax, or the tax and transfer system before the EITC expansions and welfare reform in the 1990s.

In work in progress we are currently exploring the role of the intensive margin model, the wedge between the micro and the macro elastisity, as well as the job finding elasticity. Furthermore we are working on quantifying the welfare losses stemming from the earlier reforms during the Great Recession.

6 Conclusion

This paper revisits the debate about the desirability of the EITC versus the NIT. We establish two results. First, accounting for involuntary unemployment in models of optimal taxation affects conclusions about the sign of the participation tax for low-skilled workers. Second, we show that it is important to estimate how behavioral responses vary over the business cycle. Simply observing that "welfare to work" policies are effective when labor demand is strong does not imply they are effective when labor demand is weak.

Our results have implications for welfare programs during the Great Recession. In particular they suggest that the reforms may have looked much better during the strong labor markets during the 1990s and early 2000s. However as we entered the great recession in particular, labor supply elasticities decreased. This manifested itself in particular in a sharp drop in employment rates among single mothers. To the extent that these were involuntary job losses, this may have come with substantial welfare losses to this demographic group.

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Table 1: Descriptive Statistics

	Full Sample	Low Unemployment	High Unemployment
Demographics			
Age	34.69	34.69	34.69
Frac Child < 18 yrs	0.299	0.299	0.298
Frac Child < 5 yrs	0.103	0.101	0.106
Num of kids welfare elig	0.521	0.518	0.525
Years of Education	13.15	13.16	13.14
HS Dropout	0.132	0.125	0.140
HS Graduate	0.323	0.329	0.315
Educ > HS	0.545	0.546	0.545
Fraction Black	0.189	0.172	0.208
Fraction Hispanic	0.115	0.0941	0.141
Lives in Central City	0.393	0.349	0.446
Tax Variables			
1 - ATR:15k	0.797	0.793	0.803
Real Maximum EITC thdsp	1479.8	1495.4	1460.8
Max TANF/AFDC	1432.3	1385.1	1489.7
Labor Market Variables			
Employment Rate	0.749	0.772	0.721
State unempp rate	5.647	4.367	7.206
6-mo change in unemp	0.0753	-0.0500	0.228
12-mo change in unemp	0.143	-0.159	0.509
Number of Observations	702753	385821	316932

Notes: Variable Means for Single Women from Current Population Survey 1984-2011 March and Outgoing Rotation Group. March CPS data spans 1984-2011, outgoing rotation groups span 1994-2010.
Low and High unemployment restrict data to state-year cells with unemployment below and above 5.5 percent.

Table 2: How Does the Effect of Taxes and Transfers on Employment Vary with the Unemployment Rate?

Dependent Variable: Currently Employed			
	Full Sample (1)	Edu<=12 (2)	Edu>=16 (3)
1-ATR	0.19 (0.020)**	0.25 (0.029)**	0.045 (0.013)**
12-mo Chg Unemp * 1-ATR	-0.029 (0.0054)**	-0.026 (0.0078)**	-0.028 (0.0073)**
Age	0.016 (0.00097)**	0.018 (0.0011)**	0.012 (0.00084)**
Years of Education	0.018 (0.0031)**	0.018 (0.0031)**	0.0024 (0.0032)
12 mo. Chg. State Unemp.	-0.0080 (0.0010)**	-0.0095 (0.0015)**	-0.0052 (0.0011)**
Demographics	Yes	Yes	Yes
Children	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year x Month FE	Yes	Yes	Yes
N	702753	319532	167995
R^2	0.11	0.086	0.013
Elasticity	0.21	0.32	0.040
Elasticity UR increasing	0.14	0.24	-0.015
Elasticity UR falling	0.27	0.39	0.095

Notes: * P<0.05, ** P<0.01. SE clustered at state level
Demographics include age, age squared, race, ethnicity, years of education, educational attainment and urban residence. Increasing unemployment elasticity calculated assuming 12-month unemployment change 2 SD above the mean. Falling unemployment elasticity calculated assuming 12-month Unemployment 2 SD below the mean.

Table 3: Robustness Checks: 15k Income

Dependent Variable: Currently Employed			
	Baseline Specification (1)	Controlling for Transfers (2)	Separate Tax and Welfare 1-ATR (3)
1 - ATR	0.19	0.14	
	(0.020)**	(0.019)**	
12-Month UR Change * (1-ATR)	-0.029	-0.032	
	(0.0054)**	(0.0045)**	
1-ATR of Tax Schedlue			0.24
			(0.046)**
Unemp_chg12 * Tax 1-ATR			-0.027
			(0.0054)**
Real Trans if not Working (Thsd)		-0.0052	
		(0.0012)**	
12-Month UR Change* Trans not working		0.0015	
		(0.00016)**	
1-ATR of Welfare			0.17
			(0.019)**
12-Month UR Change * Welf (1-ATR)			-0.046
			(0.0050)**
Age	0.018	0.017	0.018
	(0.0010)**	(0.0010)**	(0.0010)**
12 mo. Chg. State Unemp. (de-meaned)	-0.0080	-0.0074	-0.0080
	(0.0010)**	(0.0010)**	(0.0011)**
Demographics	Yes	Yes	Yes
Children	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year x Month FE	Yes	Yes	Yes
N	702753	702753	702753
R^2	0.11	0.11	0.11
Elasticity	0.21	0.15	0.25
Elasticity UR increasing	0.14	0.072	0.19
Elasticity UR falling	0.27	0.22	0.32

Notes: * P<0.05, ** P<0.01. SE clustered at state level
Demographics include age, age squared, race, ethnicity, years of education, educational attainment and urban residence. Increasing unemployment elasticity calculated assuming 12-month unemployment change 2 SD above the mean. Falling unemployment elasticity calculated assuming 12-month Unemployment 2 SD below the mean.

Table 4: Robustness to Controlling for Observed and Unobserved Trends

Dependent Variable: Currently Employed	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1-ATR: 15	0.19	0.19	0.19	0.19	0.19	0.20	0.20	0.20	0.27
	(0.020)**	(0.020)**	(0.020)**	(0.020)**	(0.020)**	(0.020)**	(0.020)**	(0.020)**	(0.054)**
12-Month UR Change * (1-ATR)	-0.029	-0.021	-0.021	-0.022	-0.028	-0.028	-0.029	-0.031	-0.016
	(0.0054)**	(0.0053)**	(0.0054)**	(0.0052)**	(0.0053)**	(0.0057)**	(0.0055)**	(0.0052)**	(0.0061)*
Quadradic Unemp	No	Yes	Yes	Yes	No	No	No	No	No
Cubic Unemp	No	No	Yes	Yes	No	No	No	No	No
Quartic Unemp	No	No	No	Yes	No	No	No	No	No
State FE x Unemp	No	No	No	No	Yes	No	Yes	No	No
Year FE x Unemp	No	No	No	No	No	Yes	Yes	No	No
State Trends	No	No	No	No	No	No	No	Yes	No
Year x 1-ATR	No	No	No	No	No	No	No	No	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Children	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	702753	702753	702753	702753	702753	702753	702753	702753	702753
R^2	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
Elasticity	0.21	0.20	0.20	0.20	0.21	0.21	0.21	0.21	0.29
Elasticity UR increasing	0.14	0.15	0.15	0.15	0.14	0.15	0.15	0.14	0.25
Elasticity UR falling	0.27	0.25	0.25	0.25	0.27	0.28	0.28	0.29	0.32

Notes: * P<0.05, ** P<0.01. SE clustered at state level
Demographics include age, age squared, race, ethnicity, years of education, educational attainment and urban residence. Increasing unemployment elasticity calculated assuming 12-month unemployment change 2 SD above the mean. Falling unemployment elasticity calculated assuming 12-month Unemployment 2 SD below the mean.

Table 5: Robustness to Alternative Measures of the Key Interaction Term

	Regression Estimates		Elasticities	
	(1) (A) (1-ATR)	(2) (B) (1-ATR)*Market Ind.	(3) (A)+2xσ(B)	(4) (A)-2xσ(B)
(1-ATR) x 12-mo change in unemp	0.19 (0.02)	-0.03 (0.01)	0.14	0.28
(1-ATR) x 6-mo change in unemp	0.19 (0.02)	-0.03 (0.01)	0.16	0.25
(1-ATR) x State unemp. rate	0.19 (0.02)	-0.00 (0.00)	0.18	0.22
(1-ATR) x Log Unemployment Rate	0.19 (0.02)	-0.04 (0.03)	0.18	0.23
(1-ATR) x Unemp above within-year median	0.19 (0.02)	0.04 (0.02)	0.25	0.15
(1-ATR) x Unemp above 9 pct	0.19 (0.02)	-0.08 (0.03)	0.16	0.25
(1-ATR) x Recession	0.19 (0.02)	-0.06 (0.02)	0.16	0.25
(1-ATR) x Great Recession	0.19 (0.02)	-0.09 (0.02)	0.14	0.26
(1-ATR) (taxes only) x Log Unemployment Rate	0.33 (0.05)	-0.10 (0.03)	0.32	0.47

Notes: Regressions control for age, age squared, race, ethnicity, education, urban residence, number of children, state and year x month fixed effects.
SE clustered at state level. (* P<.05, ** P<.01).

Table 6: Do Demographics Explain Why the Effect of 1-ATR Varies with the State Unemployment Rate?

Dependent Variable: Currently Employed					
	(1)	(2)	(3)	(4)	(5)
1-ATR:	0.19	0.19	0.17	0.18	0.17
	(0.020)**	(0.020)**	(0.017)**	(0.021)**	(0.019)**
12-Month UR Change * (1-ATR)	-0.029	-0.029	-0.028	-0.029	-0.028
	(0.0054)**	(0.0053)**	(0.0052)**	(0.0056)**	(0.0053)**
12 mo. Chg. State Unemp.	-0.0080	-0.0079	-0.0079	-0.0079	-0.0079
	(0.0010)**	(0.0010)**	(0.0010)**	(0.0010)**	(0.0010)**
Age * (1-ATR)		-0.0019			-0.00040
		(0.0027)			(0.0028)
Edu * (1-ATR)			-0.025		-0.024
			(0.0054)**		(0.0059)**
Black * (1-ATR)				0.095	0.090
				(0.025)**	(0.026)**
Demographics	Yes	Yes	Yes	Yes	Yes
Children	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year x Month FE	Yes	Yes	Yes	Yes	Yes
N	702753	702753	702753	702753	702753
R^2	0.11	0.11	0.11	0.11	0.11
Elasticity	0.21	0.21	0.19	0.20	0.18
Elasticity UR increasing	0.14	0.14	0.12	0.13	0.11
Elasticity UR falling	0.27	0.27	0.25	0.26	0.24

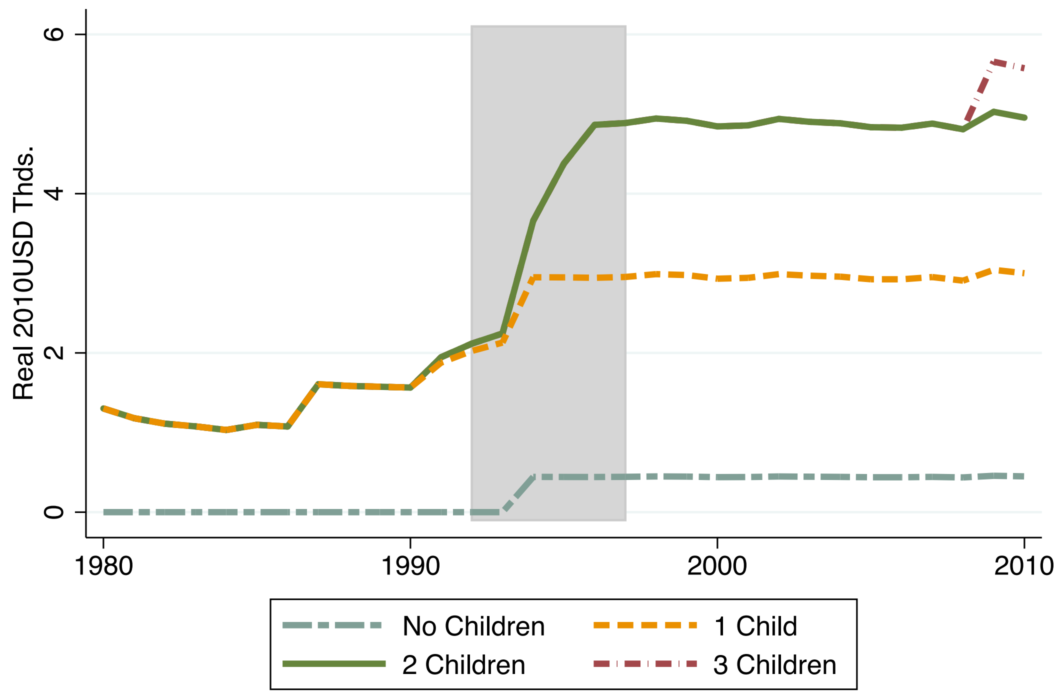
Notes: * P<0.05, ** P<0.01. SE clustered at state level
Demographics include age, age squared, race, ethnicity, years of education, educational attainment and urban residence. All interaction variables are demeaned. Increasing unemployment elasticity calculated assuming 12-month unemployment change 2 SD above the mean. Falling unemployment elasticity calculated assuming 12-month Unemployment 2 SD below the mean.

Table 7: Micro vs Macro Elasticities and Spillover Effects

	(1) Micro Elast	(2) Macro Elast	(3) Spillover Effects
1-ATR	0.20	0.10	0.20
	(0.020)**	(0.056)	(0.020)**
Mean 1-ATR in State-Year			-0.24
			(0.036)**
Demographics	Yes	Yes	Yes
Children	Yes	No	Yes
State FE	No	Yes	Yes
Year FE	No	Yes	No
Year x Month FE	No	No	Yes
Year x Month x State FE	Yes	No	No
Collapsed to State-Year Cell	No	Yes	No
srm	Yes	No	No
N	702753	1428	702753
r2	0.10	0.67	0.11
elast	0.21	0.10	0.22

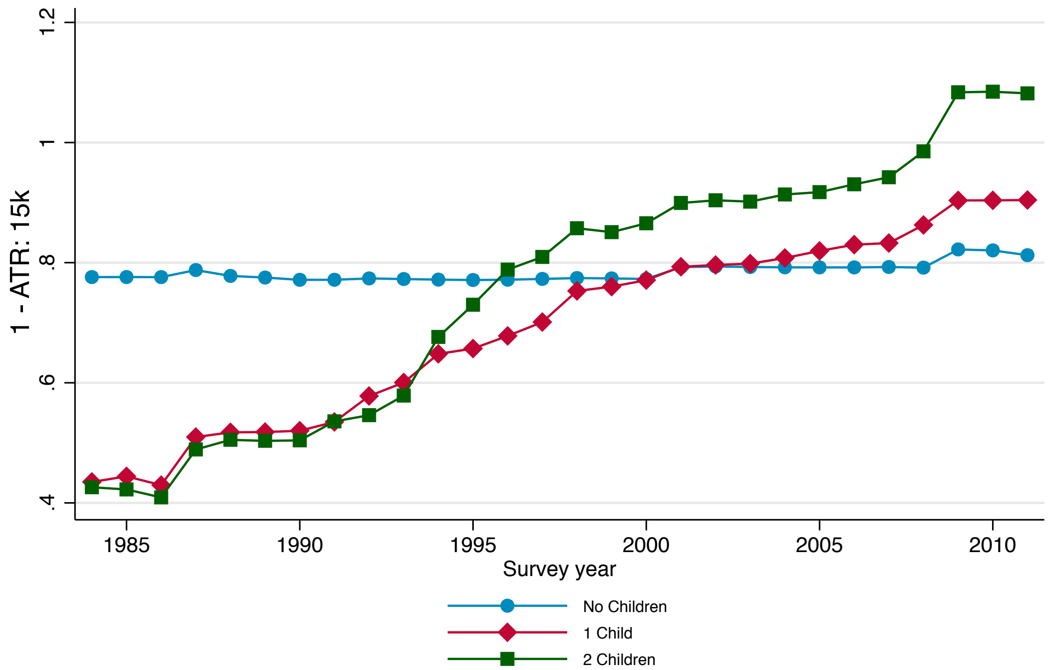
Notes: * P<0.05, ** P<0.01. SE clustered at state level
Demographics include age, age squared, race, ethnicity, years of education, educational attainment and urban residence. All interaction variables are demeaned.

Figure 1: Maximum EITC benefits

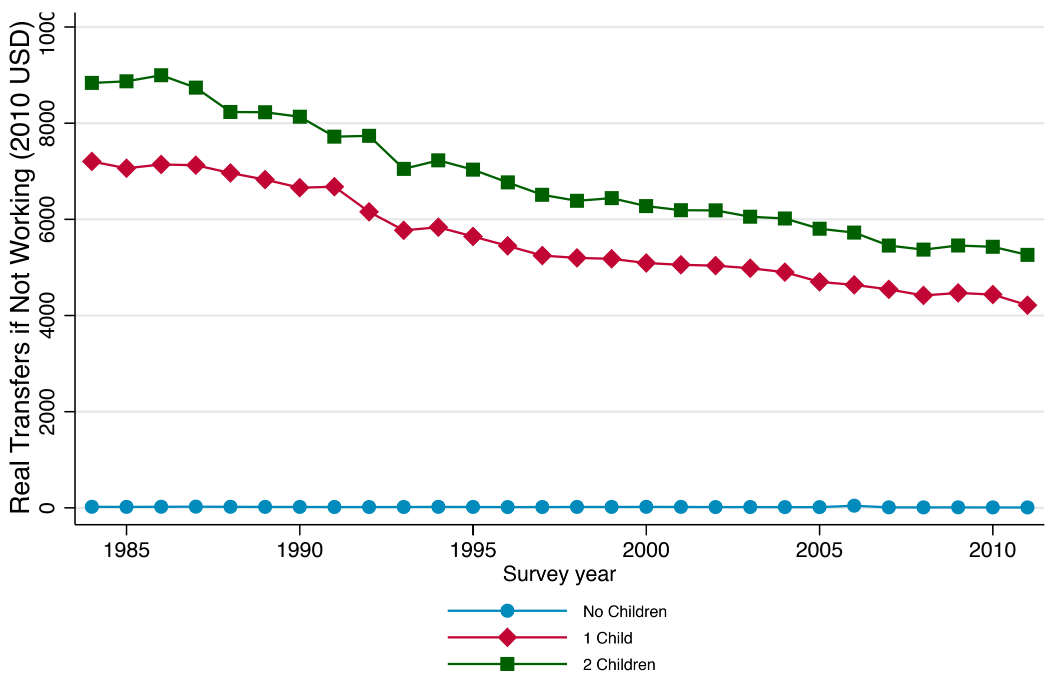


Notes: The figure shows the maximum attainable Earned Income Tax Credit, by number of children.

Figure 2: Evolution of Net of Tax Rate and Transfers at Zero Income over time



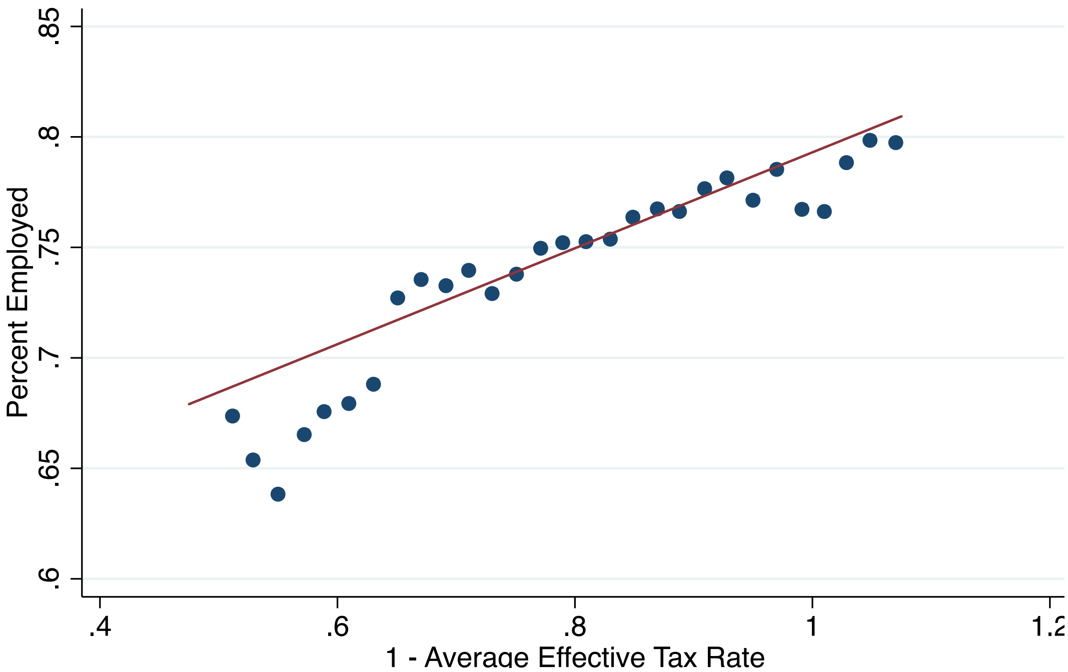
(a) Net of Tax Rate (1-ATR)



(b) Transfers at Zero Income

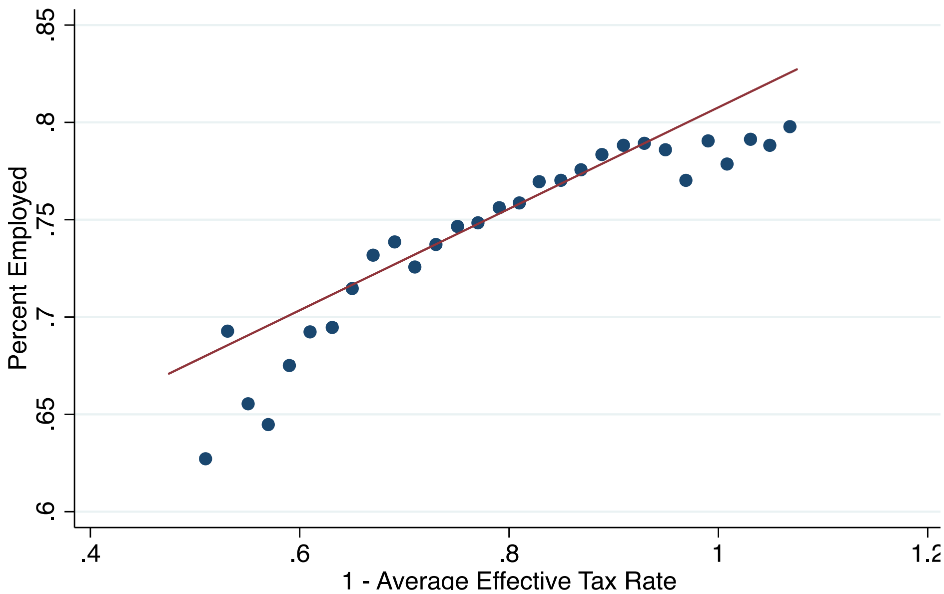
Notes: Own calculations. ATR is the average effective tax rate and individual faces at 15,000 USD yearly income. Calculations incorporate taxes and transfers from federal and state income tax, as well as TANF and AFDC benefits.

Figure 3: Non-parametric relationship between Employment and Net of Tax Rate (1-ATR)

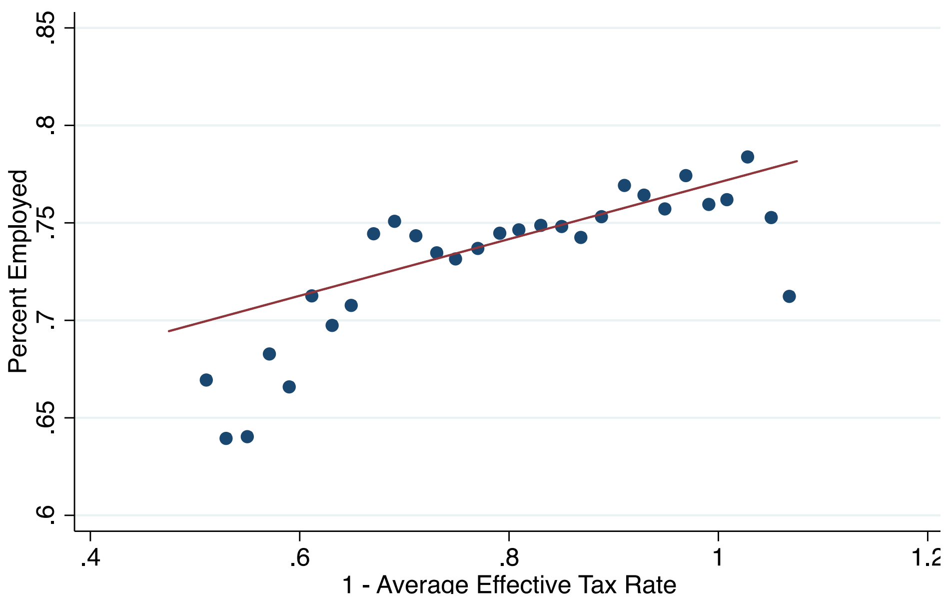


Notes: The figure shows the non-parametric relationship between the employment probability of a single woman and the net of tax rate, calculated based on TANF/AFDC and tax rules. Details see text.

Figure 4: Non-parametric relationship between Employment and Net of Tax Rate (1-ATR) by Labor Market Condition



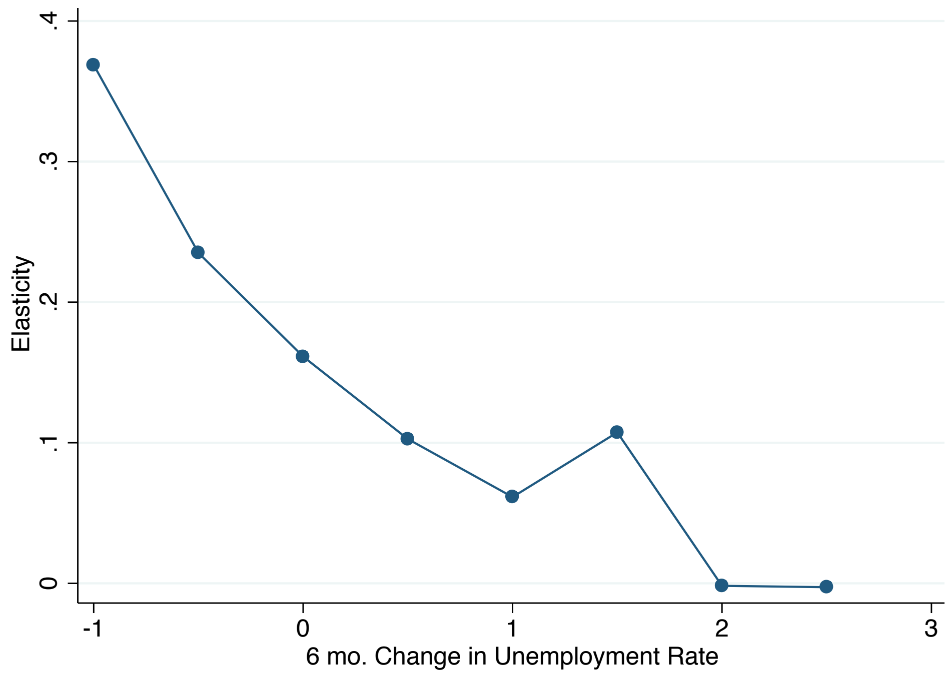
(a) Unemp. Rates Fell Over Last 12 mo.



(b) Unemp. Rates Increased Over Last 12 mo.

Notes: The figure shows the non-parametric relationship between the employment probability of a single woman and the net of tax rate, calculated based on TANF/AFDC and tax rules. The top figure shows the relationship for states and year cells where the unemployment rate (year over year) was falling, while the bottom figure shows the relationship for increasing Unemployment rates. Details see text.

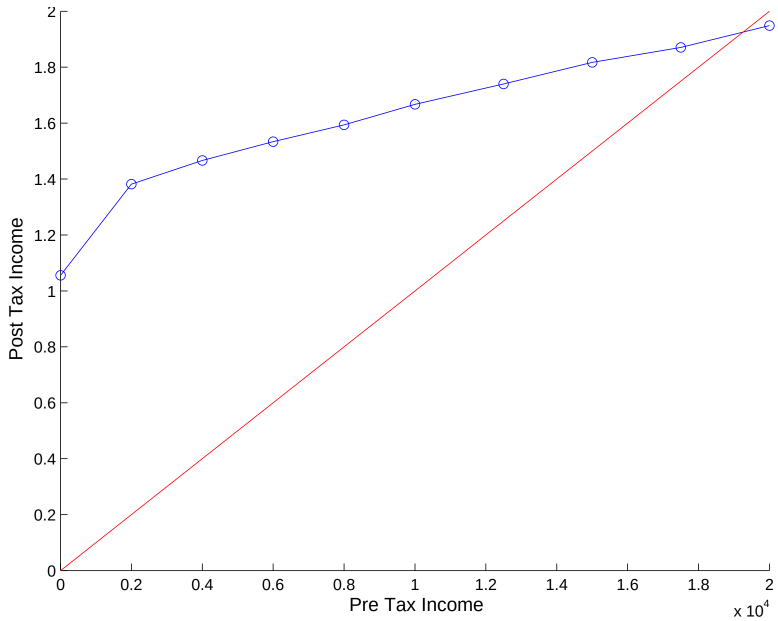
Figure 5: Estimated Labor Supply Elasticities across Levels and Changes of Unemployment.



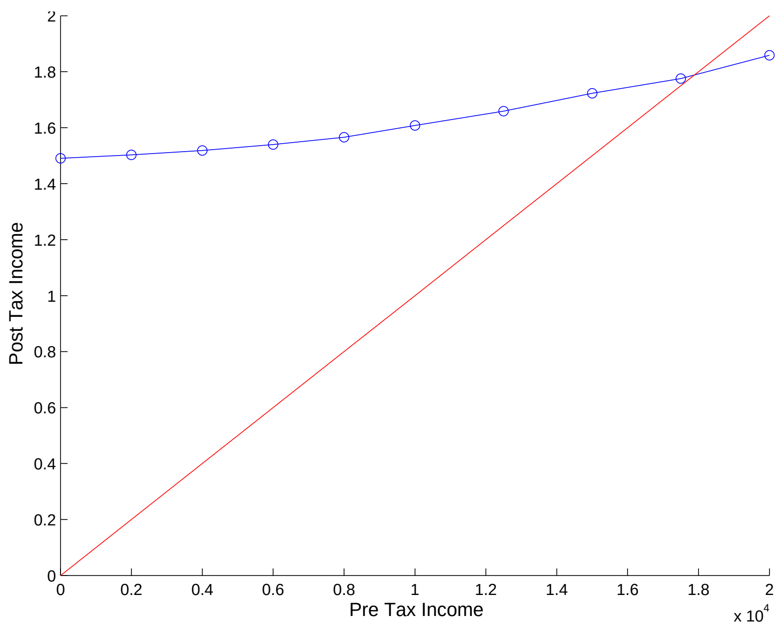
(a) Changes in Unemployment

Notes: Data CPS.

Figure 6: Optimal Tax and Transfer Schedule for high and low extensive margin labor supply elasticity



(a) Extensive Margin Labor Supply Elasticity = 0.4



(b) Extensive Margin Labor Supply Elasticity = 0.1

Notes: Data CPS.

Appendix A: Child Calculations

Data Cleaning

The data cleaning process is summarized by the following steps

1. Correctly assign the number of children the mother of a household is responsible for
2. Keep only non-military single women
3. Run TaxSim and TANF Calculator or remaining data
4. Final cleaning

1. The first data cleaning step involves assigning the number of dependent children a mother has. CPS data include the number of children a mother has living with them in the household. The problem with that data point is that it counts all individuals living with their mothers as children regardless of age. What we want is a measure of the number of children aged 18 or under living with the mother, since that is what is used for calculating many of the child tax credits and welfare benefits. To calculate the number of children under age 18 we sort the data by households and count the number of minors living in the household. Then we assign this number to the head of the household. This will not only omit children that are older than 18 but will include children living in the household who are not biological children of the mother. This is how welfare benefits are typically calculated. See Appendix A for more details about the child calculations. For tax purposes a child must under the age of 19, or be younger than 24 and in school, we recalculate the number of children for tax purposes in the same way but accounting for the children that are younger than 24 and in school.

2. After the number of children have been assigned children, males, married and military women are dropped from the sample.

3. At this point the TANF Calculator and Taxsim program are applied to the remaining sample of single women. From these programs I record hypothetical incomes and tax liabilities (or credits) at various levels of real earnings dependent on the number of children, state of residence and year: $0, $10,000, $15,000 and predicted earnings are all recorded. Predicted earnings come from a naive OLS regression of all full time working March respondents (income and full/partime status are only avaliable in the March CPS data), then the coefficients on the demographics are applied to everyone, including those who worked full time and reported income. Figure 10 displays the amount of variation in these variables we are left with.

4. Finally I drop observations if there is evidence that the data are contaminated. For instance I drop women who claim positive earnings last year but claimed they did not work last year. I also drop women who are not at least 10 years older than their youngest child.

The following cross tab shows the our calculations less the CPS data, i.e. a value of 1 means that we calculate the female head of household to be responsible for 1 more child than she claims to be her own (perhaps the child is not her biological child). A value of -1 means that the female head of household claims more of her own children in the CPS than we calculate, this is often due to biological children over the age of 18 still living at home. The following table shows our calculation minus the CPS reported number of own children:

The overwhelming majority of cases is when our calculated number matches exactly the CPS number. The '-1' category contains about 2.5% of the sample and occurs when the CPS number is one higher than what we calculate. This is the case if the mother has a 19 year old child and a minor both living in the home. The CPS number in this case would be 2 children, while we calculate only 1. Our calculation, however, does lead to some strange cases. Consider the following example household:

Here we have 3 adult women and 8 children. Each adult woman claims to have no children of their own living in the household (nchild) and each child is reported as not having their mother in the house (momloc). Many things could be going on in this household, what seems most likely is that each of these women are responsible for some of the 8 children. However our calculations will assign all 8 children to the head of household (pernum=1). This is likely over-counting her number of children.

Appendix B: Theoretical Models of Labor Demand

Search-and-Matching Model with Nash Bargaining

Let us try to see if we can connect results to the results in Lehmann et al and show that we can get their formula (see proposition 1) as a special case of our model. Aim is to show model nests alternative microfoundations. Note: a little unclear what kind of reform they consider around the optimal tax schedule. See footnote 13 of their paper for more on this.

1. k_i individuals searching for a job in occupation i, v_i vacancies in occupation i, number of matches given by $m(i, k_i, v_i)$, market tightness given by $x_i = \frac{v_i}{k_i}$.

2. Assume CRS matching function. The job-finding probability for individual searching for a job in occupation i is given by $l(i, x_i) = \frac{m(i,x_i)}{k_i}$. Similarly, let the probability of filling a vacancy be given by $q(i, x_i) = \frac{m(i,x_i)}{v_i}$. Note that $l(i, x_i) = x_i q(i, x_i)$.

3. We assume that the cost of creating a single vacancy in occupation i is $\kappa(i)$. Each firm hires a single worker and pays wage w_i. Expected profits for the firm are given by $\pi_i = q(i, x_i)\,(i - w_i) - \kappa(i)$, where i is output. At the firm level, a firm opens a vacancy if $\pi_i > 0$.

4. At the market level, we assume free-entry condition is satisfied so that firms earn 0 expected profits.[6] Firms create vacancies until the free-entry condition is met: $q(i, x_i)\,(i - w_i) = \kappa(i)$. This condition pins down market tightness x_i for a given wage: $x_i = q^{-1}\left(\frac{\kappa(i)}{i-w_i}\right)$.

5. Market tightness in turn pins down the conditional job-finding probability for a given wage $L(i, w) = l^*(i, w_i) = q^{-1}\left(\frac{\kappa(i)}{i-w_i}\right)\frac{\kappa(i)}{i-w_i}$. This is the labor demand function for an arbitrary wage level and occupation.

6

(a) This means we do not need to account for firm profits in the social welfare function.

6. We follow Lehmann et al. by assuming Nash Bargaining so that the wage maximizes $(u(w_i - T_i, i) - u(-T_0, 0))^\gamma (i - w_i)^{1-\gamma}$. [check: this might be surplus assuming unemployment benefit = welfare benefit]

7. Let us assume that the Hosios condition holds (elasticity of matching function w.r.t. unemployment equals bargaining power γ). Thus, $m(i, k_i, v_i) = A(k_i)^\gamma (v_i)^{1-\gamma}$. In this case, $q_i = \frac{m_i}{v_i} = A(x_i)^{-\gamma}$. Using the free-entry condition,

$$x_i = \left(\frac{1}{A}\frac{\kappa(i)}{i - w_i}\right)^{\frac{-1}{\gamma}} = \left(A\frac{i - w_i}{\kappa(i)}\right)^{\frac{1}{\gamma}} \tag{5}$$

This allows us to solve for labor demand:

$$L(i, w) = A\left(x_i\right)^{1-\gamma} = A^{\frac{1}{\gamma}}\left(\frac{\mathbf{i} - \mathbf{w_i}}{\kappa(\mathbf{i})}\right)^{\frac{\mathbf{1}-\gamma}{\gamma}} \tag{6}$$

8. A and $\kappa(i)$ are constants. Thus, $argmax\,(u(w_i - T_i, i) - u(-T_0, 0))^\gamma (i - w_i)^{1-\gamma} = argmax\,(u(w_i - T_i, i) - u(-T_0, 0))\,(i - w_i)^{\frac{1-\gamma}{\gamma}}$ and $argmax\,(u(w_i - T_i, i) - u(-T_0, 0))\,(i - w_i)^{\frac{1-\gamma}{\gamma}} = argmax L(i, w)\,(u(w_i - T_i, i) - u(-T_0, 0))$.

9. Define $\Sigma_i = l_i \Delta u^m_{i*}$. Then, we can re-express social welfare defined above as:

$$W = \int\limits_{M_L} \mu^m\left(\Sigma_i + u^m(-T_{-1}, -1)\right) dv(m) + \int\limits_{M_N} \mu^m u^m(-T_0, 0) dv(m)$$

1. To see what the model implies for the magnitudes of the micro and macro elasticities, we can depict the equilibrium of the model in employment and market tightness space. Landais et al (2011) show that market tightness acts as the market clearing device in search-and-matching models, since the wage is determined after workers and firms meet. From 1), we can see that market tightness does not depend on the level of employment in the model. Thus, tightness is pinned down by perfectly elastic labor demand.

2. What about labor supply? Labor supply in the model is given by $h_i^* = k_i L(i, w_i)$. Market tightness enters through k_i. In particular, $\frac{dk_i}{dx_i} > 0$ which leads to an upward-sloping supply curve in employment-market tightness space.

3. Consider an increase in T_i. This leads to more people choosing non-participation. So the labor supply curve shifts out and this response is governed by the micro elasticity. Also, the wage obtained from Nash Bargaining increases (check) and so market tightness deceases and the labor demand curve shifts down (wage also affects labor supply). The total effect is governed by the macro elasticity.

Diminishing Marginal Productivity and Rigid Wages

To be completed.