A Structural Model of Welfare, Taxes, Labor Supply and Program Participation

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We estimate a model of the joint employment, hours, and program participation decisions of single women that generalizes aspects of Keane and Moffitt (1998). We examine the 1984-1996 period when welfare incentives were well summarized by a single period budget constraint. These years also include dramatic change in tax and welfare policy that sharply altered labor supply and program participation incentives of single mothers. These policy changes were associated with large changes in the employment, hours and program participation of single mothers. Using 13 years of Current Population Survey (CPS) data, we identify parameters using changes in program incentives that differentially affected individuals with different numbers and ages of children, in different states and years. We compare this identification strategy to the usual strategy which relies on cross-sectional wage variation to identify structural parameters. We use a nonparametric approach to selection, allow for an arbitrary relationship between wages and work preferences, and account for the under-reporting of welfare receipt in CPS data.
1. Introduction

• In recent years, research has suggested that there is no satisfactory way to examine labor supply when individuals face nonlinear budget sets. As a result, the volume of work on labor supply has dwindled and the degree of progress has slowed down. This state of the literature can be attributed to the following:

• Budget sets are nonlinear, often highly so. Nonlinearity leads labor supply to be a complicated nonlinear function of preferences, wages and all of the tax parameters that determine the budget set.

• Budgets sets are often nonconvex. Nonconvexity is the dominant case for low skilled single mothers due to welfare and the Earned Income Tax Credit (EITC). Nonconvexity of the budget set or fixed costs leads to labor supply that is discontinuous in wages and tax parameters.

• These observations imply that ad hoc solutions like the local linearization of choices around the current one and the use of IV, are likely to give us badly biased estimates because the error terms in such equations are complicated functions of all tax and transfer parameters and individual attributes. Furthermore, local linearization and the use of IV is only a reasonable approximation when people are making local choices, thus excluding nearly all of the interesting cases such as participation choices or large changes in hours.

• The alternative methods, kinked budget set techniques using maximum likelihood estimation, have been criticized for their distributional and functional form assumptions and require a huge programming investment. Probably most importantly, these methods have been criticized for imposing restrictions that are rejected by the data (MaCurdy et al. 1990, MaCurdy 1992).

• One should think of this last critique as arguing that the way nonlinear budget estimation has been implemented is problematic. The critique does not apply to methods based using direct utility function comparisons of alternative choices. In addition, this critique does not correctly separate economic and statistical assumptions. Any approach which begins with continuous demand or examines one budget segment at a time is not appropriate with either nonconvex preferences or nonconvex budget sets (Heim and Meyer, in progress).
Our approach here:

- We use a single internally consistent model to examine the employment, hours and program participation choices of single women over the 1984-1996 period.

- We combine the focus on exogenous variation in incentives that characterizes good natural experiments with the emphasis of structural modeling on economic relationships between variables and economically motivated functional forms.

- The structural approach is closest to that of Keane and Moffitt (1998) and Hoynes (1996) in that we begin with a direct utility function and assume individuals choose from a discrete set of alternatives.

- The natural experiment aspect of the paper focuses on using separate pieces of the variation in after-tax wages to identify wage effects. Specifically, we consider welfare benefits and taxes separately from wages. We also consider the variation due to changes in state taxes, changes in tax treatment of different size families, and due to differences in living costs.

- If you are going to take wages to be exogenous, you will inexorably conclude that there is a substantial wage elasticity for single women. On the other hand, we may be observing characteristics of jobs per se rather than people's decisions. Part-time jobs may just pay poorly. If one thinks of jobs as coming with a bundle of attributes including hours and wages, then estimating elasticities using this cross-sectional wage variation will lead to biases.

- Since the approach is utility based we can do policy simulations and welfare analyses.

- The approach incorporates the complexity of welfare programs and state and federal income taxes as well as individual characteristics.

- We have 4 hours choices and one program with stigma or transaction costs.

- We take a smoothed version of the model to be the truth (this aids computation).

- We use fixed hours and wage points which also simplifies the model. One would
need to do very computationally intensive numerical integration otherwise because the after-tax and after-transfer incomes are complicated functions of hours and wages. One still needs to do numerical integration, but fixed hours and wage points simplifies the integration.

- We also use a nonparametric selection correction to account for the fact that we only observe the wages of those that have chosen to work. The true wage distribution is easily identified because we have observed wages for most people combined with a very sophisticated model of selection with many obvious exclusions restrictions. The programs we examine have large effects on employment, but little effect on pre-tax wages.
2. Summary of Institutional Background

Program Changes 1984-1996:

• EITC: there was a ten-fold increase in credits in real dollars.

• Medicaid: there was a 77 percent increase in the number of recipient children.

• Welfare Benefits: benefits for those not working were cut, but the implicit tax rates for those working were also cut.

• Welfare Waivers: most states implemented some type of waiver.

• Training: programs were expanded and their focus changed.

• Childcare: four big federal programs were added between 1988 and 1990.

• The combined effect of these program changes greatly increased the incentive for single mothers to enter the workforce and, in most but not all cases, made welfare receipt less attractive. The effects of the program changes on hours are often unclear, but the EITC is predicted to reduce hours among the working.

Outcome Changes:

• Employment. Coincident with the policy changes were large increases in the employment of single mothers between 1984 and 1996.

• Welfare. The pattern of welfare receipt had a more complicated pattern. Caseloads increased greatly through the middle of this period. The increases then reversed in 1994 when a precipitous drop in the number of AFDC cases began.

• 1996 was also the first year that most of those who received welfare also worked.
3. Previous Research

* Work on the EITC:

• Eissa and Liebman (1996) examine the effects of the Tax Reform Act of 1986 on single mothers using March CPS data. This paper is the first to directly examine the effects of the EITC on employment.

• Meyer and Rosenbaum (1999a) examine the effects of tax, welfare, Medicaid, training and childcare program changes over the 1984-96 period on the employment of single mothers. This work uses the CPS merged Outgoing Rotation Group data as well as the March CPS data.

• Both of these papers find large effects of the EITC on employment. Meyer and Rosenbaum also find substantial effects of recent changes in AFDC benefits, waivers, childcare and training programs.

• Both of these papers also examine the effects of the EITC on hours and surprisingly find no evidence of a decrease in hours. Neither uses a very attractive model of hours.

• Ellwood (1998) and Bishop (1998) are other recent papers that look at employment effects of the EITC but not hours.
Work on Welfare Caseloads:

- Levine and Whitmore (1999) attribute over 40 percent of the steep decline in the national AFDC caseload over the 1992-96 period to economic growth and almost one-third to waivers, particularly those that sanction recipients who do not comply with work requirements. They find that the AFDC benefit level has little effect on caseloads.

- Martini and Wiseman (1997) criticize the way waivers are measured and suggest that caseload declines are likely to lead to waiver applications, rather than the other way around.

- Blank (1997) finds important effects of macroeconomic conditions and AFDC benefit levels on caseloads. She finds that welfare waivers are associated with caseload declines, but concludes that “these waivers are correlated with other changes occurring (and even preceding) their implementation that are causing caseloads to decline in states that seek waivers. It is hard to determine how much [of] these effects might be due to the actual program implementation of the waiver, but it is surely no more than half…”

- Ziliak et al. (1997) argue that economic conditions were the primary cause of recent caseload declines and that waivers played a much smaller role.

- There are more recent papers by Blank and Ziliak. The recent Ziliak paper argues that the caseload changes have been entirely due to economic conditions.

- These studies have relied on aggregate welfare participation data and been unable to fully account for individual characteristics and variables that differ with family size and composition. This work also does not account for many important programs that affect single mothers. In particular, these studies do not account for federal and state earned income tax credits (EITCs).

- Moffitt (1999) uses CPS micro data to look at the effect of waivers on employment, hours and wages. He finds that waivers are associated with increases in employment and hours.
4. Data and Descriptive Statistics

- We use 13 years of Current Population Survey (CPS) Data. The CPS is fairly standard and its big sample size (well over 100,000 observations on single women) is an advantage. At some point, we will probably also use the Survey of Income and Program Participation (SIPP). In recent years SIPP data seems to have less under-reporting of welfare receipt than the CPS. But the SIPP is a smaller dataset and to use it appropriately one needs to account for the dependence between observations from successive interviews.

**What Provides the Comparisons which Allows a Researcher to Estimate Program Effects?**

EITC: we compare changes in employment of single mothers who were subject to many changes in state and federal tax incentives (EITC, standard deduction, personal exemption, state taxes) to changes in employment for single childless women. We then compare changes over time for single mothers (again the same provisions differed by number of children; the EITC depends greatly on whether you have one or two children beginning in 1994). We also look at states with different tax schedules and EITCs of their own. Finally, we interact these changes with state living costs (a $3600 EITC check goes further in Arkansas).

AFDC: There are differences across states in the level of benefits, the amount of earnings that is disregarded, the rate at which benefits are reduced after the disregard and the additional benefit for increments to family size. These parameters also change over time.

Medicaid: On top of differences across states and over time that determine AFDC eligibility, there were many required and optional expansions of benefits to families with different incomes levels and different child ages. These expansions were very different in different states.

Waivers: Waivers are present only in some states during some periods.

Training: States differed in the expenditures allotted them and the fraction they spend. States also emphasize different types of training. The overall expenditures and emphasis changed over time.
Child Care: States differed in the expenditures allotted them and the fraction they spent. A dollar in child care funds went further in some states (with lower wages) than in others.

- **Table 1:**
  Means reported separately for single mothers and single women without children.

- **Table 2:**

  Mean values of outcome variables and policy variables for selected years between 1984 and 1996.

  We report the outcome variables and the tax variable separately for single mothers and single women without children.

  Employment rose faster for single mothers than for single women without children.

  Program participation among all single mothers was higher in the late 1980s and early 1990s than earlier, and then dropped sharply at the end of the period.

  AFDC Participation among non-working single mothers was higher in the early 1990s than it was before or since. You should think of takeup as being about 80 percent since half of the gap between the numbers in the table and 100 percent is probably under-reporting.
5. The Model and Likelihood Function for Employment, Hours and Program Participation

We assume utility is a function of income $Y$, hours worked in the month $H$, an indicator for welfare participation $P$, individual characteristics $z$, a vector of parameters $\theta$, and a vector of unobserved characteristics $\varepsilon$. Thus, we can write

$$U = U(Y, H, P, z(W), \theta, \varepsilon).$$

Let $U$ take the Stone-Geary form for now (we may generalize this later), i.e.

$$U = \frac{\beta}{(1+\beta)} \ln(\mu - H - \rho P - \varphi E) + \frac{1}{(1+\beta)} \ln(Y + \eta),$$

where $\rho$ captures transaction costs or stigma measured in hours, and $\varphi$ captures the fixed costs of working. If hours exceed zero, $E=1$, otherwise $E=0$. We allow tastes for leisure to vary in the population, i.e.

$$\beta = \exp\{z'\gamma + \beta_0 + \beta_1 \varepsilon\}$$

so that the utility function becomes

$$U = \frac{\exp\{z'\gamma + \beta_0 + \beta_1 \varepsilon\}}{1 + \exp\{z'\gamma + \beta_0 + \beta_1 \varepsilon\}} \ln((\mu - H - \rho P - \varphi E) + \frac{1}{1 + \exp\{z'\gamma + \beta_0 + \beta_1 \varepsilon\}} \ln(Y + \eta).$$

We assume that a woman participates in Food Stamps if and only if she participates in AFDC. We assume that a woman always participates in Medicaid if eligible (we could relax this later and add a second transaction cost term).

Income is pre-tax earnings minus taxes, plus AFDC and Food Stamps, plus Medicaid benefits, plus the value of employer provided health coverage, plus other income. We calculate the earnings, taxes, and benefits for a given individual incorporating family composition (number and ages of children), and characteristics of state and federal policies at the time.

We allow the coefficients on the different components of income to differ,
since income from different sources may be valued differently. In equations,

\[ Y(H, P) = wH + \alpha_1 \text{taxes} + \alpha_2 \text{AFDC} \text{ and Food Stamp benefits} \]
\[ + \alpha_3 \text{Medicaid coverage valued at cost} \]
\[ + \alpha_4 \text{employer provided health coverage valued at cost} + \text{other income,} \]
where \( w \) is the hourly wage.

Note: we may need to do something about other income here as there will be people with income from other sources that we probably don’t want to ignore.

All of the terms preceded by alphas are a function of \( wH \). AFDC plus Food Stamp benefits are also a function of \( P \), i.e. they are zero if \( P=0 \).

We calculate real income and benefits across states using a cost of living index which depends on state housing costs. Work and hours decisions should depend on the real return to work, not the nominal return.

Likelihood Functions:

\( H_i = \) hours worked per month by person \( i \), \( H_i \in \{H^1, H^2, ..., H^j\} \), where \( J \) is the number of possible hours values.

\( P_i \in \{0,1\}, 1 \) if person \( i \) participates in welfare and 0 otherwise.

\( W_i = \) the wage of person \( i \), \( W_i \in \{W^1, W^2, ..., W^K\} \), where \( K \) is the number of possible wage levels.

Then the likelihood for a sample of observations indexed by \( i=1,...,M \) with observed hours \( H_i = h \), participation indicator \( P_i = p \), and, if \( h>0, W_i = w \), is

1. \( \log L = \sum_{i|H_i=0} \log \{ \text{Prob}[H_i=0, P_i=p]\} \]
   \[ + \sum_{i|H_i>0} \log \{ \text{Prob}[H_i=h, P_i=p| W_i=w] \text{Prob}[W_i=w]\} \]

Let \( \text{Prob}[W_i=W^K] = \omega^K \). We will estimate \( \{\omega^1, \omega^2, ..., \omega^{K-1}\} \). For computational reasons, we parameterize \( \omega^K = \exp\{w^K\} / (1 + \sum_{k=1}^{K-1} \exp\{w^k\}) \), \( k=1,..., K-1 \) with \( \omega^K = 1 / (1 + \sum_{k=1}^{K-1} \exp\{w^k\}) \).

We numerically integrate over the distribution of \( \varepsilon \) by taking random draws from
its distribution. This method is usually called simulated maximum likelihood estimation. Let $N$ be the number of draws of $\varepsilon$ for each observation.

\[
\text{Prob}[H_i = 0, P_i = p] = \sum_{n=1}^{N} \sum_{k=1}^{n} \omega^n \{ \text{Prob}[U(Y, 0, p, X, \theta | \varepsilon^n, W^n) > U(Y, h', p', X, \theta | \varepsilon^n, W^n)] \text{ for all } h', p' \text{ not equal to } 0, p}.\]

For $h$ not equal to zero we have

\[
\text{Prob}[H_i = h, P_i = p | W = w] = \sum_{n=1}^{N} \sum_{k=1}^{n} \{ \text{Prob}[U(Y, h, p, X, \theta | \varepsilon^n, w) > U(Y, h', p', X, \theta | \varepsilon^n, w)] \text{ for all } h', p' \text{ not equal to } h, p}.\]

We can approximate $\text{Prob}[U(Y, h, p, X, \theta | \varepsilon^n, w) > U(Y, h', p', X, \theta | \varepsilon^n, w)]$ for all $h', p'$ not equal to $h, p$ as

\[
\exp[U(Y, h, p, X, \theta | \varepsilon^n, w)/\tau]/\{\sum_{j} \sum_{m} \exp[U(Y, H_l, m, X, \theta | \varepsilon^n, w)/\tau]\} \text{ for small } \tau.\]

As $\tau \to 0$ this expression goes to 0 or 1.

This modification is equivalent to adding an extreme value error term to the utility of each alternative. This computational trick smooths the likelihood function and thus speeds convergence. Now, we can calculate analytic derivatives to speed convergence (and check our programming). Alternatively, one can consider the additional extreme value error terms as optimization error and take the model estimated to be the true model.

We calculate the values of the variables AFDC if work, Taxes if work, Medicaid if work for all the earned income levels equal to each possible $w$.

The full vector of parameters to be estimated is

\[
\theta = (\alpha_1, ..., \alpha_4, \beta_0, \beta_1, \gamma, \rho, \varphi, \omega^1, ..., \omega^{k-1}), \text{ where } \gamma \text{ is a vector.}\]

We include dummies for each wage value in $z$ so that parameters are not identified through differences in wages across individuals.

We also consider modifications of this model to account for the underreporting of welfare receipt. Comparisons of CPS and administrative reported by Richard Bavier (1999) indicate that only 76.4 percent of those receiving welfare report it in the CPS for the years 1987 through 1996 (we use an 80 percent figure because the reporting rate was higher in the early years and our sample includes observations
beginning in 1984). Underreporting is likely to bias upwards estimates of \( \rho \), the transaction costs and stigma of welfare participation.

We can account for underreporting by reinterpreting \( P_i \) to be the observed participation status, while \( \bar{P}_i \) is the true participation status. Also let \( R \) be the fraction of those receiving welfare that report welfare receipt.

Then, in the likelihood expressions one replaces

\[
\begin{align*}
\text{Prob}[H_i = 0, P_i = 1] & \quad \text{with} \quad \text{Prob}[H_i = 0, \bar{P}_i = 1] \times R \\
\text{Prob}[H_i = 0, P_i = 0] & \quad \text{with} \quad \text{Prob}[H_i = 0, \bar{P}_i = 0] + \text{Prob}[H_i = 0, \bar{P}_i = 1][1-R]
\end{align*}
\]

Analogously, for \( h \) not equal to zero one replaces

\[
\begin{align*}
\text{Prob}[H_i = h, P_i = 1 | W = w] & \quad \text{with} \quad \text{Prob}[H_i = h, \bar{P}_i = 1 | W = w] \times R \\
\text{Prob}[H_i = h, P_i = 0 | W = w] & \quad \text{with} \quad \text{Prob}[H_i = h, \bar{P}_i = 0 | W = w] \\
& \quad + \text{Prob}[H_i = h, \bar{P}_i = 1 | W = w][1-R]
\end{align*}
\]

This form of the probabilities has been simplified by assuming that the probability that someone who is not receiving welfare reports receiving welfare is sufficiently small that it can be set to 0.

We set \( P = 0 \) for those observations reporting welfare receipt despite wage and hours such that welfare income is zero. We also assume that those with income below $3,000 are underreporting income and set other income to that amount which brings their total income up to $3,000.

6. Results (preliminary and incomplete)

Main results

Demographics: Older workers, whites, those with more education, fewer kids, fewer young kids all put a greater weight on income rather than leisure. Some of the results may be due to effects that work through wages rather than preferences, and thus need to be checked after wage distributions which differ by some of these same dimensions are allowed.
Basic patterns:

Higher wages increase employment, hours and decrease welfare participation.

Higher welfare benefits reduce employment and hours and increase welfare participation. Welfare is usually valued at close to a dollar for dollar the same as wages.

There is a substantial stigma or transaction cost of welfare participation, with a magnitude generally on the order of at least several hundred hours a year.

The other policy variable coefficients make sense. More childcare and training and time limits on welfare increase employment and decrease welfare participation.

The key result that has puzzled us is the coefficient on taxes. When we examine the full model, we get a coefficient on taxes that says that taxes are valued a dollar for dollar like wages, but it has the wrong sign. When we crudely look at just the employment decision (by having only one hours choice), taxes have an even larger coefficient but of the correct sign (with an asymptotic normal stat of over 130).

Allowing for underreporting of welfare receipt tends to make the estimate of stigma or transaction costs lower. This result makes sense since the estimate of transaction costs is in large part driven by women who look like they should participate and yet don’t. The number of such women is reduced by the correction for underreporting which accounts for the fact that many of those not reporting welfare receipt are nevertheless receiving it.

Allowing the mean of preferences to vary by wage level seems to be too much to ask of the data. The preference terms have odd (but precisely estimated) coefficients and they cause other parameters to move in peculiar directions.

The two main samples, single women with and without children and only single mothers, tend to give very similar results.

The nonparametric selection correction works well, i.e. the probabilities of the different wage values are estimated precisely. Usually, the selected wage distribution of workers stochastically dominates the distribution for all women, working and nonworking.
There is plenty of data to separate out the effects of wages, taxes and welfare benefits.

Some tentative general conclusions about structural labor supply estimation from someone who has mostly done nonstructural work:

Structural estimation is more work because of the programming.

It is more likely that structural estimates have mistakes since it is harder to detect mistakes, conceptual or programming. Part of the reason for this difficulty is that it is much harder to check if your programs are right and this is even more true as your programs get more complicated. It is also hard to compare your results to simple patterns in the data or results from other studies.

It is much, much harder to see what the sources of variation are that are driving the results, i.e. what are the key sources of identification.
References


