Frictional Adjustment to Income Tax Incentives: An Application to the Earned Income Tax Credit *

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Abstract

This paper finds that individuals respond to changes in tax incentives by switching jobs, and changing the jobs that they are willing to accept when unemployed. The finding is consistent with a labor market model characterized by hours constraints and search frictions. When matching the evidence, the model indicates substantial differences between the short and long-run responses of single mothers to the Earned Income Tax Credit (EITC). The long-run effect on employment, for example, is 7 percentage points larger than in the short-run. The implications are immediate for the measurement of tax incidence and deadweight loss: the welfare effects of the tax are more than double relative to those that can be measured from short-run responses. These findings generate a stark comparison to the commonly used frictionless benchmark.

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1 Introduction

The neoclassical model of labor supply is a workhorse tool for tax policy analysis. Supposing that workers can freely adjust their hours of work, given a particular wage, the model offers structural elasticities that decide the optimality of tax schedules (Mirrlees, 1971; Diamond, 1998; Saez, 2001), and measure the deadweight loss from income taxes (Harberger, 1964; Feldstein, 1999).

This paper considers the implications of two important departures from the neoclassical model. First, jobs may be accompanied by constraints on hours worked (Altonji and Paxson, 1988; Chetty et al., 2011). When this friction prevails employed workers will respond to changes in tax incentives by switching to new jobs, while unemployed workers will change the jobs they are willing to accept.[1] Second, these adjustments are constrained by the stochastic arrival of new job opportunities in a labor market characterized by search frictions. The contribution of this paper is to document novel evidence of these frictions, and to derive positive and normative implications by matching the evidence to a dynamic model of on-the-job search with hours constraints, finding meaningful differences between short and long-run responses to tax changes.

An empirical design borrowed from Chetty, Friedman and Saez (2013) uses the response of single mothers to the Earned Income Tax Credit[2] to provide evidence of the key mechanisms of adjustment. This approach relies on a "sharp bunching" measure as a proxy for awareness of the tax: the excess mass of earnings reported by self-employed workers at the refund-maximizing kink in the EITC schedule. Chetty, Friedman and Saez (2013) comprehensively validate this measure as a proxy for local

[1]Workers may also take second jobs (Paxson and Sicherman, 1996), which is not the focus of the paper but is borne out by the upcoming empirical analysis.

[2]The EITC is the largest cash transfer program for low income families at the federal level (Meyer, 2010). The credit implicitly targets single mothers through the income ranges and the dependence on children that determine eligibility.

awareness of the EITC. Under the assumption that differences in outcomes between eligible and ineligible individuals are otherwise stable, any difference in the differences across counties with different levels of awareness is attributable to the tax credit. The first part of the paper derives difference-in-differences (DD) estimates from the Current Population Survey (CPS) using a method that explicitly accounts for measurement error in the awareness proxy. It specifies a finite number of county "types" with different rates of awareness and estimates a finite mixture model, yielding estimable moments from the data for each county type. The difference in differences between high and low awareness counties yields estimates of the EITC's effects, suggesting that it lead to increases in employment, increases in the monthly employer-employer (EE) transition rate, and an increase in the fraction of low wage, part-time jobs accepted out of unemployment. A regression analysis that more closely follows Chetty, Friedman and Saez (2013) indicates the same pattern of results. Importantly, the documented responses are not fully consistent with predictions from the neoclassical model.

The next stage of the analysis introduces a labor market model with two key frictions to match the evidence.[3] First, jobs are characterized by a wage and a fixed number of hours that cannot be adjusted in response to changes in incentives. Second, jobs are not frictionlessly allocated but are instead encountered randomly by both employed and unemployed workers according to an undirected search technology. In the model, an earnings subsidy distorts individuals' preference rankings over wage and hours combinations, resulting in an increase in the rate at which employed workers switch to new jobs, as well as a decrease in the wages that workers are willing to accept out of unemployment. In the estimated model, this will result in an increase in workers taking low-wage, part-time jobs out of unemployment.

In order to interpret the sharp bunching evidence, eligible workers in the model

[3]To our knowledge, the first paper to structurally estimate a model with these features was Shephard (2017) who also used the model to study the effect of a tax credit in the UK.

become aware of the tax credit according to an exogenous probability that varies by county type. The estimation method defines types using the same measurement error model from the first stage, which relied on excess bunching in earnings among the self-employed. The decisions of these self-employed workers are not modeled, and the bunching in their reported earnings serves only for the purposes of measurement of local awareness. Also consistent with the first stage approach, economic primitives are permitted to vary by county type so as not to let underlying covariation confound inference, analogous to the inclusion of a county fixed effect in the linear DD model. Relative to the linear model, the labor market model imposes more structure on the data and does not explicitly require the same variation to identify tax effects. It also does not imply the strong assumption of stable differences between eligible and ineligible individuals across counties, nor does it require this assumption for inference. The model therefore offers an alternative empirical device for evaluating tax effects while (1) remaining consistent with the original evidence; and (2) enabling normative conclusions. In accordance with the first stage empirical analysis, the model assumes that awareness is an exogenous stochastic process.

The paper delivers its main conclusions by using counterfactual simulations from the estimated model to evaluate the short and long-run effects of the EITC. This exercise finds the EITC has resulted in a 13 percentage point increase in employment for single mothers in the long-run, a full 8 percentage points higher than the effect of the tax after 6 months, which serves as the "short-run" benchmark in the analysis. The difference between short and long-run effects has immediate implications for measurement of welfare. The model's estimated long-run effect of the EITC on total welfare is worth an average of 11.5% of consumption. If the short-run effects of the tax on labor market allocations were mistakenly interpreted as the long-run effects, one would conclude that the EITC lead to an increase in welfare worth 5% of consumption, less than half the true effect. To further unpack the result, a second counterfactual starts by deriving a sufficient statistic formula for steady state welfare effects of a marginal expansion in the EITC. The formula clarifies that, much like the neoclassical model, a link still exists between the reduced form effects of a tax change and welfare calculations. Rather, the key difference arises in the two models' alternative implications for the *timing* of measurement. The model with frictions exhibits important differences in tax effects over time. Accordingly, the measured welfare effects of a marginal expansion in the EITC are much (i.e., 200%) larger when using long-run effects compared to short-run.

A final counterfactual exercise extends the model to allow for endogenous wage-setting through posted wages, as in Burdett and Mortensen (1998). *Ex ante*, the addition of firm monopsony power in wage-setting could affect conclusions by allowing (1) for taxes to potentially correct for market inefficiencies; and (2) for pass-through of tax changes to wages. In practice, the model extension does not greatly affect the long-run positive and normative effects, echoing the findings of Shephard (2017).

The paper relies and builds upon on two adjacent literatures. The first has sought to estimate the response of individuals to changes in tax incentives and the EITC in particular (Eissa and Liebman, 1996; Meyer and Rosenbaum, 2001; Grogger, 2003; Hotz and Scholz, 2006; Chetty, Friedman and Saez, 2013; Kleven, 2021).[4] The second conducts normative tax policy analysis either by using estimated tax responses as direct inputs into deadweight loss formulae (Eissa, Kleven and Kreiner, 2008*b*; Feldstein, 1999) or by directly estimating structural models of the labor market (Shephard, 2017; Bagger, Moen and Vejlin, 2021). Methodologically, this paper combines approaches by disciplining the structural model with direct evidence on its key causal mechanisms. It also provides a link by showing that while the normative effects of the tax can still be measured by behavioral responses using a collection of sufficient statistics, this collection is (1) very large and imposes high demands on the data; and

[4]While the literature overwhelmingly finds strong positive employment effects, Kleven (2021) argues that prior estimates that rely on expansions of the credit for identification may be confounded by contemporaneous welfare reform. Since this paper does not rely on time-varying credits for identification, such a critique does not apply.

(2) vulnerable to misleading conclusions when measured with short-run responses.

The lessons of the paper's main counterfactuals echo prior arguments that frictions can complicate the measurement of behavioral elasticities (Dickens and Lundberg, 1993; Kahn and Lang, 1991; Chetty, 2012; Kreiner, Munch and Whitta-Jacobsen, 2015). This paper provides direct evidence of highly salient frictions at play and considers them in a dynamic environment that allows for a distinction between short and long-run responses. Such a distinction turns out to be important for measurement.

The rest of the paper is structured as follows. Section 2 documents empirical evidence on the response of employment, employer-employer transitions, and wages to the EITC. Section 3 describes the frictional labor market model. Section 4 discusses identification of the model, describes the estimation procedure, and presents the model estimates. Section 5 performs counterfactuals that depict the implications of hours constraints and search frictions in the labor market for policy analysis and measurement. Lastly, Section 6 offers concluding thoughts.

2 Evidence of Frictional Adjustment to the EITC

2.1 Empirical Strategy

This section describes the empirical strategy used to examine the response of single mothers in the United States to the EITC.[5] The empirical analysis is built around the following model of outcomes for individual i in county $c(i)$:

$$\mathbb{E}[Y_i|K_i, A_i] = \mu_{c(i)} + \beta K_i + \gamma K_i A_i \tag{1}$$

where Y_i is the outcome of interest for individual i, $K_i \in \{0, 1\}$ indicates whether individual i has children (and is therefore eligible for the tax credit), $A_i \in \{0, 1\}$ indicates that individual i is aware of the tax, and $\mu_{c(i)}$ are county-specific fixed effects. In place of A, which is not assumed to be observable, let $\pi_{c(i)}$ be the fraction

[5] Details of the EITC structure are provided in Appendix D.

of individuals who are aware of the tax in county $c(i)$. Conditioning out A_i gives the estimable model specification:

$$\mathbb{E}[Y_i|K_i] = \mu_{c(i)} + \beta K_i + \gamma K_i \pi_{c(i)}. \tag{2}$$

The model specifies that while outcomes may vary systematically across counties, differences between eligible ($K = 1$) and ineligible ($K = 0$) individuals remain stable. Accordingly, the effect of the tax, γ, is identified by any systematic relationship between the difference in these differences and the level of awareness $\pi_{c(i)}$.

The rate of awareness π_c is itself not perfectly observable, but rather noisily observable through a county-level and time-dependent bunching measure, B_{ct}.[6] Assume that the error is additively separable with a measurement equation:

$$\log(B_{ct}) = \kappa_0 + \kappa_1 \log(\pi_{ct}) + \epsilon_{ct}. \tag{3}$$

The main set of results, which will discipline the upcoming quantitative model, are built on a finite mixture model that specifies that each county $c = 1, 2, ..., C$ belongs to one of a finite number of types, $k(c) \in \{1, 2, ..., K\}$ with an awareness level that is stable over time such that $\pi_{ct} = \pi_{k(c)}$. This assumption is consistent with the upcoming model, which requires that the economy is in steady state. Section 2.1.1 below describes how variation in awareness over time may be used in a linear regression framework to test for tax effects in a similar spirit.

With repeated measurements, the vector $\pi = \{\pi_1, ..., \pi_K\}$ is identified along with the population proportions of each county type. Under a location and scale normalization, the effect of the tax, γ, is also identified. Assuming that bunching is proportional to awareness (i.e., $\kappa_1 = 1$) is sufficient for a scale normalization, while the estimated model will also adopt the location normalization that $\pi_1 < \pi_2 < ... < \pi_K = 1$.

[6]Section 2.2.2 describes the construction of this measure.

2.1.1 An Alternative Strategy

An alternative approach to explicitly estimating the latent distribution of awareness levels is simply to specify:

$$Y_i = \mu_{c(i)} + \eta_{t(i)} + \beta K_i + \tilde{\gamma} K_i B_{c(i)t(i)} + \zeta_i \tag{4}$$

which includes time fixed effects (η) and allows for bunching to potentially measure variation in awareness over time as well as across counties. Here the effect of the tax is not identified but, under appropriate assumptions, the coefficient $\tilde{\gamma}$ is sufficient for signing the effect of the tax and testing the null hypothesis of no effect ($\tilde{\gamma} = 0$). This approach also more closely mirrors the methodology originally proposed by Chetty, Friedman and Saez (2013) to use the bunching measure. The model in this paper focuses on steady state equilibria and so variation in awareness over time is not well-articulated. This motivates a focus on results that use the finite mixture model. However, the specification above will prove useful for validating the results using a more familiar empirical strategy and allows for testing their robustness.

2.2 Data

2.2.1 Outcomes and Demographics

The *Current Population Survey* (CPS) provides the necessary data on employment outcomes and transitions to implement the empirical analysis. The main analysis sample contains all observations of unmarried women between the ages of 18 and 50 from the years 2003 to 2008. The basic monthly files provide information on employment status, hours, marital status, age, education, number of children in the household, and county of residence. As is typical, the short panel structure of the CPS also allows one to identify labor market transitions, including employer-employer (EE) transitions.[7] Information on earnings and wages is also available for a subset of

[7] A survey item that asks respondents whether they are still at their previous job provides this information.

sample members in the Outgoing Rotation Group (ORG). In this analysis, employed individuals are those who report having a job regardless of whether they worked last week or not. Individuals are said to be working full-time (FT) if their usual weekly hours of work exceeds 30. Flood et al. (2018) provide cleaned data extracts with these variables. Table 1 reports descriptive statistics for the subsample of unmarried women.

Table 1: Descriptive Statistics

Employed (%)	68.91
Full-time (%)	79.95
Employer-Employer (EE) transitions (%)	3.24
One or more children (%)	35.79
Two or more children (%)	18.31
Mean Age	31.38
Weekly hours worked	37.82
Mean Wage ($/hr)	14.38
High school or less (%)	42.85
4+ years college (%)	21.61
Num. observations	1,054,182
Num. individuals	244,022

This table presents descriptive statistics from the CPS sample of unmarried women, aged 18-50, from the years 2003 to 2008. See main text for variable definitions.

2.2.2 Sharp Bunching Measure

Chetty, Friedman and Saez (2013) provide bunching data for replication at the 3-digit zip code level. Since 3-digit zip code boundaries are neither a subset nor a superset of county boundaries, the 2010 Census Zip Code Tabulation Area (ZCTA) to County relationship file[8] provides population weights which can be used to create a weighted measure. Let w_{czt} be the fraction of the population in county c that resides within the 3-digit zip code z. The county-level bunching measure is then a population weighted average of the 3-digit zip code bunching measure:

$$B_{ct} = \sum w_{czt} B_{zt}$$

where the weights w_{czt} by definition sum to one within each county c, and B_{zt}, the bunching measure for each zip code z and year t, are taken directly from the replication data. Clearly, this weighted average does not perfectly recover the true level of bunching in a county. However, since the original bunching measure acts purely as a proxy for awareness, one should expect the newly constructed proxy to adequately serve the same purpose.

2.3 Estimation

Under the assumption that the measurement error term, ϵ_{ct}, in equation (3) is normally distributed with mean zero and variance σ_ϵ^2, a maximum likelihood routine provides consistent estimates of the measurement parameters $(\kappa_0, \kappa_1, \sigma_\epsilon^2)$, in addition to the vector of awareness rates by county type (π) and the population proportion of county types. Table 2 reports the maximum likelihood estimates using three county types $(K = 3)$. Using three types is sufficient to demonstrate the key empirical facts while keeping the interpretation of results and estimation of the model tractable.

Define the posterior weight, q_{ck}, as the posterior probability that county c is of type k given the estimates of the measurement model and the sequence of bunching measures, $B_c = \{B_{ct}\}_{t=2003}^{2008}$. Formally

$$q_{ck} = P[k(c) = k | B_c, \hat{\pi}, \hat{\kappa}_0, \hat{\sigma}_\epsilon].$$

[8] Data can be found at https://www.census.gov/geographies/reference-files/time-series/geo/relationship-files.html

Table 2: Measurement Model Estimates

Parameter	Estimate	Std. Error
σ_ϵ	0.200	0.002
κ_0	-1.880	0.007
π_1	0.330	0.003
π_2	0.560	0.005
π_3	1.000	0.000
$P[k(c) = 1]$	0.370	0.009
$P[k(c) = 2]$	0.410	0.010

This table reports estimates of the measurement model described by equation (3) with three county types ($K = 3$). Standard errors are calculated from 100 bootstrap trials at the county level.

For any outcome Y_i, where i indexes observational units, moments can be estimated for each county type as:

$$\mathbb{E}[Y_c|\widehat{k(c) = k}] = \frac{\sum_i Y_i q_{c(i)k}}{\sum_i q_{c(i)k}}. \tag{5}$$

The next section documents the difference-in-differences analysis at the county-type level using this formula for county specific means.

2.4 Results

Following equation (2), the expression

$$\hat{\gamma} = \frac{1}{1-\hat{\pi}_1}\Big[\Big(\mathbb{E}[Y|\widehat{k(c) = 3}, f = 1] - \mathbb{E}[Y|\widehat{k(c) = 3}, f = 0]\Big) - \Big(\mathbb{E}[Y|\widehat{k(c) = 1}, f = 1] - \mathbb{E}[Y|\widehat{k(c) = 1}, f = 0]\Big)\Big] \tag{6}$$

Table 3: Difference-in-Differences Estimates of EITC Effects

	E	EE	EU	FT	MJH
$\hat{\gamma}$	0.042	0.011	-0.002	-0.021	0.019
95% Conf. Interval	[0.004, 0.099]	[0.002, 0.019]	[-0.008, 0.005]	[-0.060, 0.019]	[0.004, 0.033]
Std. Error	0.025	0.005	0.003	0.020	0.008
P-value	0.051	0.011	0.725	0.856	0.009

This table reports estimates using equation (6), where moments are calculated using estimates from the finite mixture model using (5). Confidence intervals, standard errors and p-values are calculated via county-level bootstrap with 100 replacement samples.

delivers an estimate of the effect γ of the tax on each outcome Y. Table 3 reports estimates of the tax's effects on five outcomes of interest. The results suggest that the net effect of the EITC on employment and EE transitions was positive, with no statistically significant impact on separations (EU) or hours arrangements (FT).

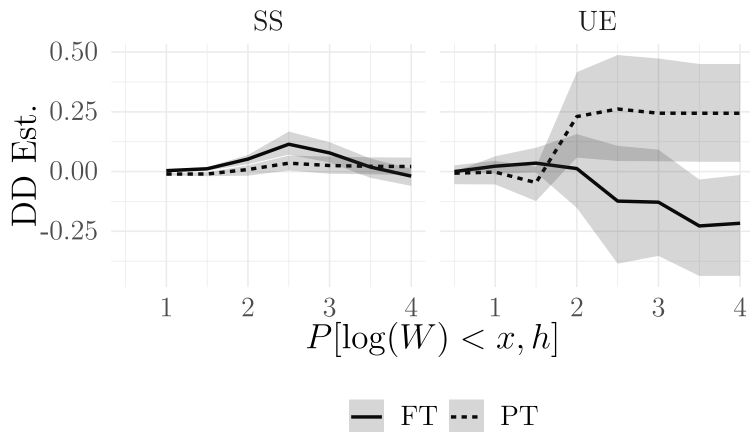
Estimates suggest that the EITC has increased employment by 4.1 percentage points and EE transitions by about 1 percentage point. While the first finding is consistent with many models of labor supply, the second suggests that workers respond to changes in tax incentives by switching jobs, which is only consistent with a narrower class of models. There is evidence of a similar mechanism at play in the United Kingdom, where the introduction of a working tax credit led to an hours increase for single mothers that occurred mainly through job-switching (Blundell, Brewer and Francesconi, 2008). The job-switching phenomenon suggests that workers must find new jobs in order to respond to changes in tax incentives. The upcoming quantitative model will accommodate this fact by introducing hours constraints on jobs that can only be found through undirected search.[9]

Table 3 also presents evidence that multiple job holding (MJH) increased in response to the EITC. This provides further evidence of the salience of hours constraints that inhibit the response to tax changes within a job, echoing the findings of Tazhitdinova (2022). Due to tractability issues, the upcoming model does not allow individuals to hold multiple jobs and cannot speak to these effects, but it does nevertheless support the model's underlying assumptions.

While employment and job-to-job transitions are the primary outcomes of interest, the upcoming model also has implications for the effect of the tax on wages. Accordingly, Figure 1 shows estimates of the effect of the tax on the joint distribution of wages and hours arrangements. The left panel shows estimates of the effect in the cross-section, which in the model will be interpreted as the wage distribution in steady state (SS). The right panel shows the estimated effect on the joint distribution of wages accepted out of unemployment (i.e., those for which a UE transition has been recorded). Starting with the so-called "steady state" distribution, the estimated effect in the right tail simply restates the finding from Table 3, that there is little effect on average hours arrangements in total. However, the left panel shows that there is also a shift to the left in wages for full-time workers. The right panel of Figure 1 suggests that the EITC causes part-time jobs to be accepted relatively more frequently out of unemployment (UE), and that this effect is concentrated among jobs that pay less than $7 per hour.

[9]Strictly speaking, hours constraints alone would be sufficient to rationalize job-switching. The introduction of search frictions allows interpretation of the evidence in an environment with well-known features of the labor market such as involuntary unemployment and a positive rate of EE flows that is unrelated to changes in incentives.

Figure 1: Difference-in-Differences Estimates of Tax Effects on Wages and Hours



This figure depicts the difference-in-differences estimate (6) of the effect of the EITC on the joint distribution of wages and hours. The left panel shows estimates of the effect on the cross-sectional or "steady state" (SS) distribution. The right panel shows effects on the distribution for jobs accepted out of unemployment. Ribbons indicate a 95% bootstrapped confidence interval from 100 county-level replacement samples.

2.5 Additional Analysis and Robustness

By estimating the underlying distribution of awareness and interpeting differences in differences accordingly, the previous section provides evidence on the effect of the EITC that can be cleanly linked to the quantitative labor market model below. The regression approach outlined in equation (4) is a natural approach to supplement this evidence and demonstrate that it is not simply an artifact of a complicated statistical procedure. This approach also more closely mirrors the design of Chetty, Friedman and Saez (2013), although it requires stronger assumptions.[10] Table 7 presents the estimates from regression specification (4) with additional county, time, and education

[10] Chetty, Friedman and Saez (2013) use individual fixed effects, implying that first births are the key source of variation in eligibility.

fixed effects. It replicates the finding that employment and EE transitions increase in response to the tax, while there is no significant effect on overall rates of full-time employment.

Although there is no direct test of the identifying assumptions of this paper's empirical analysis, an imperfect robustness test is available through the use of a placebo treatment. Consider a new treatment group as women with three or more children. For the analysis period in this paper, having three or more children did not additionally change tax credit entitlements relative to having two children.[11] Under the assumption that they are similarly affected by the tax, this implies no additional effect of an interaction between bunching and the indicator for having three or more children. If on the other hand, differences in employment or EE transitions are driven by a systematic relationship between awareness and selection into fertility by propensity to work or switch jobs, then this could potentially explain a positive and significant interaction between bunching and the placebo group. Clearly this is an imperfect test, since heterogeneity in the effect of the tax could explain any differences equally well. Nevertheless, Table 8 presents evidence using estimates of the regression

$$Y_i = \mu_{c(i)} + \eta_{t(i)} + \beta_1 K_i + \tilde{\gamma}_1 K_i B_{c(i)t(i)} + \beta_2 K_{3,i} + \tilde{\gamma}_2 K_{3,i} B_{c(i)t(i)} + \zeta_i \tag{7}$$

where $K_{3,i}$ is a binary variable indicating the presence of three or more children in the household. With estimates of $\tilde{\gamma}_2$ not statistically different from zero, Table 8 indicates no evidence of additional tax impacts for this placebo treatment group.

3 Model

In order to interpret the empirical evidence, this section describes a model in which workers receive job offers that entail both a wage and a fixed number of hours of work, as in Shephard (2017). It includes a mild extension of this framework in order to model different rates of tax awareness in the data.

[11]A differential EITC credit rate for families with three children was only introduced in year 2009.

3.1 Environment and Demographics

Let there be K separate economies, one for each county type. Time is continuous and each economy k is populated by a unit mass of individuals who either have ($f = 1$) or do not have ($f = 0$) children. Individuals with children are considered eligible for the tax credit.[12] Individuals with children become aware of the tax at a constant rate ξ_k. At a constant rate ζ, individuals with children become childless and exit the economy. They are replaced by an equal fraction of unemployed individuals with children who are unaware of the tax. The steady state fraction of eligible individuals who are aware of the tax in county k is therefore:

$$\pi_k = \frac{\xi_k}{\xi_k + \zeta}.$$

3.2 Preferences and Technology

Individuals in the economy are either unemployed ($e = 0$), employed in part-time work ($e = 1$) or employed in full-time work ($e = 2$). Employed individuals receive earnings w, while unemployed individuals have zero earnings ($w = 0$). Consumption is dictated by a government transfer function T that depends on earnings, fertility status, and whether or not the individual is aware of the tax credit. Individuals are summarized by the state variable (a, f, e, w) and receive a flow utility

$$Z = T(w, a, f) - \alpha e$$

while discounting the future exponentially at rate r. The cost of work, α, is heterogeneous and drawn from a population distribution $H(\cdot|k, f)$. Individuals are not aware of the awareness process, and hence this process does not feature in preferences or behavior.

[12] While individuals without children are technically eligible for a small credit (7.65%), the amount is small relative to families with children (34% and 40% for families with one child and two children, respectively), between 2003 and 2008.

Individuals receive job offers at a constant poisson rate that depends on their employment status, $\lambda_{e,k}$.[13] Each job offer is drawn from a joint distribution $F_{W|k}$. $F_{W|k}(w, e)$ is the joint probability that the job offer has hours e with earnings less than or equal to w. Jobs are exogenously destroyed at a constant rate δ_k.

3.3 Solution and Empirical Content

In this model, individuals make only one decision: whether or not to accept a job offer. To characterize the empirical content of the model, it is sufficient to characterize this decision along with the steady state distribution of workers over states. To economize on notation, the exposition below suppresses dependence of parameters and endogenous objects on county type, k. In the model, workers care only about the flow utility of each job, and so it useful to rewrite the job offer distribution in terms of these flow utilities for a specific worker type:

$$F_{Z|\alpha}(z|\alpha, c, a, f) = F_W(T^{-1}(z + \alpha, a, f), 1) + F_W(T^{-1}(z + 2\alpha, a, f), 2).$$

Under this change of variables, an individual's job search can be summarized by a reservation utility, z^*_α, which defines the kind of job that leaves a worker indifferent between working or remaining unemployed. It solves:

$$z^*_\alpha = T(0, a, f) + (\lambda_0 - \lambda_1) \int_{z^*_\alpha} \frac{\tilde{F}_{Z|\alpha}(z)}{r + \zeta f + \delta + \lambda_1 \tilde{F}_{Z|\alpha}(z)} dz$$

where $\tilde{F} = 1 - F$ for any distribution F in the rest of the paper. This formula is standard in models with undirected search and so a derivation is left to Appendix E.1. The first term in this equation, $T(0, a, f)$, captures the flow utility to an unemployed worker with awareness status a and fertility status f. The second term captures the option value of remaining unemployed, which is summarized by the expected value of the next job offer multiplied by the difference in the rate at which this offer arrives,

[13]The rate at which part-time and full-time employed individuals in county type k receive job offers is constrained to be the same (i.e., $\lambda_{1,k} = \lambda_{2,k}$).

$(\lambda_0 - \lambda_1)$. Thus, while unemployed, a worker accepts any job that provides a flow utility greater than z^*_α. Employed workers, on the other hand, accept any job that offers a utility z' that is higher than the utility z that they derive from their current job. This occurs with probability $\tilde{F}_{Z|\alpha}(z)$. This completely characterizes the flows of a given type of worker between employment states.

Estimation of the model assumes that the economy is in *steady state*: that workers are distributed over employment states such that all flows between states are balanced. Appendix E.2 provides an analytic characterization of this steady state[14], but the explicit details are not particularly central to the paper's results.

Two observations are helpful in understanding the effect of the EITC on employment and EE transitions. First, since the EITC subsidizes earnings, it shifts the distribution of job utilities ($F_{Z|\alpha}$) for eligible workers to the right. This makes all jobs more acceptable, increasing the probability $\tilde{F}_{Z|\alpha}(z^*_\alpha)$ that any draw from the offer distribution is acceptable. This in turn leads to an increase in the probability that unemployed workers find acceptable jobs, resulting in an increase in employment.[15]

Second, the EITC both *lengthens* and *distorts* the job ladder, resulting in an increase in EE transitions. Formally, let $u \in [0, 1]$ be a particular worker's percentile ranking of each job type by utility, conditional on the job being acceptable. Letting G be the steady state distribution of this worker type over percentiles, the EE rate is

$$\lambda_1 \tilde{F}_{Z|\alpha}(z^*_\alpha) \int_0^1 G(u)du.$$

This is the rate at which offers arrive, λ_1, times the probability that the offer is acceptable, $\tilde{F}_{Z|\alpha}(z^*_\alpha)$, times the probability that the acceptable new offer dominates the current job (the integral term). By making more jobs acceptable out of unemployment, the EITC increases the second term and effectively lengthens the job ladder. In other words, workers accept jobs from further down the wage distribution, which

[14] See Burdett and Mortensen (1998) and Bontemps, Robin and Van den Berg (1999) for two canonical examples of steady state characterization in models that also feature wage posting.

[15] In steady state, employment is $\lambda_0 \tilde{F}_{Z|\alpha}(z^*_\alpha)/(\zeta + \delta + \lambda_0 \tilde{F}_{Z|\alpha}(z^*_\alpha))$.

increases the probability they will subsequently move. Since the EITC also distorts individuals' utility rankings over jobs once they become aware of it, the steady state distribution G lies to the left of where it would be under full awareness. This increases the third term in the equation. In other words, workers' position u on the job ladder gets shifted down, on average, once they become aware of the tax credit, which increases the probability of moving.

3.4 Exogenous Wages

One interpretation of the offer distributions F_W is that each wage offer reflects the marginal productivity of a worker at that job, such that F_W is the exogenous distribution of marginal productivities. This would be true, for example, under the islands model setup of Lucas and Prescott (1978). In such a framework, while job opportunities stochastically arrive, wages are still set in competitive equilibrium. The later counterfactual exercises take this framework as the benchmark to evaluate the dynamic positive and normative implications of the EITC.

3.5 Endogenous Wages

The assumption that wages are competitively set and exogenous is strong. It implies that all taxation results in deadweight loss,[16] and that there is no pass-through of tax changes to wage offers. This section describes an alternative setup in which firms have some degree of monopsony power. It relaxes the implication that all taxation results in inefficient allocations of workers to jobs, and allows for firms to adjust their wage-setting policies in response to tax changes. It also allows for spillovers to occur from eligible to ineligible individuals: a phenomenon that would violate key assumptions of the difference-in-differences approach and contaminate estimates of tax effects.

[16] Of course, the EITC is still welfare improving if it results in reductions in this deadweight loss, as in Eissa, Kleven and Kreiner (2008*b*).

Firms are ex-ante heterogeneous. Let $\Gamma(p, e)$ be the distribution of firms over productivities and hours arrangements. The steady state profit for a firm with productivity p and hours arrangement e equals the measure of employed workers, $l(w, e)$, times the profit per worker:

$$\Pi(p, w, h) = (pe - w)l(w, e).$$

As described in prior work (Burdett and Mortensen, 1998; Bontemps, Robin and Van den Berg, 1999) an equilibrium is a wage offer function $\varphi(p, e)$ such that:

1. φ maximizes profit, Π, for each pair (p, e), and

2. the offer distribution, $F_W(w, e)$, is consistent with φ and Γ, i.e.,

$$F_W(w, e) = \int \mathbf{1}\{\varphi(e, h) \leq w\}\Gamma(dp, e).$$

For the case in which φ is monotonic in p for all hours arrangements, the above expression simplifies to:

$$F_W(w, e) = \Gamma(\varphi^{-1}(w, e), e). \tag{8}$$

Given the assumption of undirected search, workers must be evenly distributed over all firms offering wage w and hours e, such that we get:

$$l(w, e) = \frac{g_W(w, e)}{f_W(w, e)}$$

where g_W is the unconditional density of workers at jobs of type (w, e) and f_W is the density of offers for jobs of type (w, e). Since there are two types of workers, with and without children, the unconditional density over jobs should be written as:

$$g_W(w, e) = \frac{\pi(1 - u^0)g_W^0(w, e) + (1 - \pi)(1 - u^1)g_W^1(w, e)}{\pi(1 - u^0) + (1 - \pi)(1 - u^1)}$$

where π is the fraction of women in the economy without children and g^f is the steady state density of women with fertility status f.

4 Identification and Estimation

Identification of models of undirected search is generally well understood. Shephard (2017) and Bontemps, Robin and Van den Berg (1999) show nonparametric identification in two settings that are very closely related to this paper. It is therefore unsurprising that the model here is also nonparametrically identified, but the result does provide an important contrast with the difference-in-differences (DD) approach that Section 2 used to document responses to the EITC. The linear model used by the DD approach contains free parameters with which to exactly fit all effects of the tax. Identification of that model consequently requires both the imposition of parallel trends as well as variation in awareness of the tax to identify those parameters. By contrast, the labor market model of Section 3 requires neither parallel trends no variation in tax salience for identification. The effects of the tax are instead implied by deeper structural parameters of the model, which can be identified by a single cross-section of wages, employment states, and employment transitions. In this sense, the model is overidentified and additional variation provides validating evidence.

Nevertheless, estimation of the model loosely follows the logic of the DD approach by using the sample of women without children to estimate the bulk of the model's parameters. Women with children differ from women without children only in terms of the distribution of work costs, H. Since the model is non-linear, it will generally not exhibit parallel trends in outcome variables even when deeper parameters of the model do. In this sense, the model relaxes the assumptions under which the effects of taxes can be forecasted by imposing additional structure in the relationship between the two groups. Section 4.4 will examine untargeted moments from the estimation process.

Two parameters are externally set. The quantitative model assumes a monthly discount rate of $r = 0.005$, while the exit rate of eligible individuals ζ is set to 0.0016. At this value, the annual fraction of individuals who become ineligible matches the fraction of households whose youngest child is 19 and hence will be ineligible next year.[17] We further assume throughout that all observations are sampled independently from a period in which each market k is in steady state.

Lastly, the government transfer function T, which depends on earnings w, fertility status f, and whether or not the individual is aware of the tax a, is defined as follows:

$$T = w + aEITC(w, f) - 0.15 \max\{w - D - EX(f), 0\}$$

where D is the standard deduction, EX is the personal exemption, and EITC represents the tax credit. In estimation, we use the parameters from year 2005.

4.1 Identification

The model for women without children ($f = 0$) is otherwise non-parametrically identified by a cross-section of wages, hours, and employment transitions. With its short panel dimension and subsample of worker hours and wages, the CPS dataset that earlier offered evidence on the effects of the EITC provides the requisite sample information. Thus, the wage and hours offer distribution ($F_{W,k}$), rate parameters ($\lambda_{0,k}, \lambda_{1,k}, \delta_k$), and distribution of work costs for women without children ($H(\cdot|k, f = 0)$) are all identified for each county type k. Appendix B provides the formal argument for nonparametric identification.

Imposing some parametric structure on the offer distribution, F, and the work cost distribution, H, makes estimation more practical. In each county type, the offer distribution is a mixture of two log-normal distributions:

$$F_{W|k}(w, e) = \rho_k F^1_{w|k}(w) + (1 - \rho_k) F^2_{w|k}(w)$$

where ρ_k is the probability of getting a part-time job offer and $F^e_{W|k}(w)$ is the cdf of wage offers for jobs with hours e. Let $\mu_{w,e,k}$ and $\sigma_{w,e,k}$ indicate the mean and standard

[17] This fraction is calculated using all unmarried women in the 2003 American Community Survey between the ages of 18 and 50.

deviation of these log-normal distributions for hours arrangement e and county type k.[18]

The distribution of work costs, $H(\cdot|k,f)$, also takes a log-normal distribution with parameters $\mu_{\alpha,k,f}$ and $\sigma^2_{\alpha,k}$. While the mean is allowed to vary by county type (k) and fertility (f), the variance is fixed within county type. As such, the only remaining parameter to be identified is the difference in the average cost of work for women with children relative to women without children. This is duly identified by average differences in rates of employment within county types.

4.2 Estimation

This section outlines a simulated method of moments (SMM) procedure that selects moments bases loosely on the identification argument. The E-M procedure in Section 2.3 yields consistent estimates, $\hat{\pi}_k$, of the rate of awareness in each market type. The steady state relationship between π and ξ can then be inverted to get an estimate of the rate at which individual's become aware of the tax:

$$\hat{\xi}_k = \frac{\hat{\pi}_k \zeta}{1 - \hat{\pi}_k}.$$

Also from the E-M procedure, the posterior weights q_{ck} over county types allow consistent estimation of any moment using equation (5).

The full vector of moments $g_{N,k}$ for each county is derived using mainly women without children. It includes (1) the cross-sectional (i.e., steady state) distribution of these individuals over employment states; (2) the rate at which they transition from employment to unemployment; (3) distributional wage moments for each hours arrangement in the cross-section; and (4) distributional wage moments for each hours arrangement among individuals who have just transitioned out of unemployment.

[18] Although the wage offer distribution can be summarized parametrically, a distribution over firm types $\Gamma(p,e)$ can be inverted using equation (8) to rationalize the observed distribution. This is further discussed in subsection 4.3.

Under the prevailing parametric restrictions this is more than sufficient to identify all of the model's parameters, except for the triple $(\mu_{\alpha,1,k})_{k=1}^{3}$ which indexes the average difference (for each county) in the costliness of work for women with children relative to those without children. The inclusion of the average rate of employment for women with children in each county type ensures the identification of these parameters.

The result is a vector of empirical moments g_N that consistently and asymptotically normally estimate their population counterparts, which can be written as $g(\Omega^*)$, where Ω^* are the "true" parameters of the model. Using simulation to evaluate the mapping $g(\Omega)$, a SMM procedure produces estimates by solving:

$$\hat{\Omega} = \arg\min(g_N - g(\Omega))'W(g_N - g(\Omega)),$$

where W is the inverse of a diagonal matrix, where the jth component of the diagonal equals the variance of the jth component of g_N. Table 4 and Figure 2 lists all of the moments used for the SMM procedure.

4.3 Estimating Firm Productivities

The version of the model with endogenous wages requires an estimate of Γ, the distribution of firm productivities. For any point (p, e) in the space of productivities and hours arrangements, the estimated equilibrium wage offer function is:

$$\hat{\varphi}(p, e) = \arg\max \hat{\Pi}(p, w, e)$$

where the symbol $\hat{}$ indicates that the model estimates are used in calculation. Following equation (8), Γ can be estimated non-parametrically as:

$$\hat{\Gamma}(p, e) = \hat{F}_W(\hat{\varphi}(p, e), e).$$

4.4 Model Estimates

Table 4 reports targeted moments from the SMM procedure and the model's fit of these moments at the parameter estimates. The model does a very good job in fitting the employment rates and employment-to-employment transition rates for all county types. The model also fits reasonably well the distribution of part-time and full-time accepted wages, with only a few discrepancies for the wages accepted out of unemployment.[19] While the model does not have parameters designed to explicitly target EE rates for women with children across county types, Table 5 shows that the model largely matches those untargeted moments.

Table 4: SMM Procedure - Auxiliary Moments

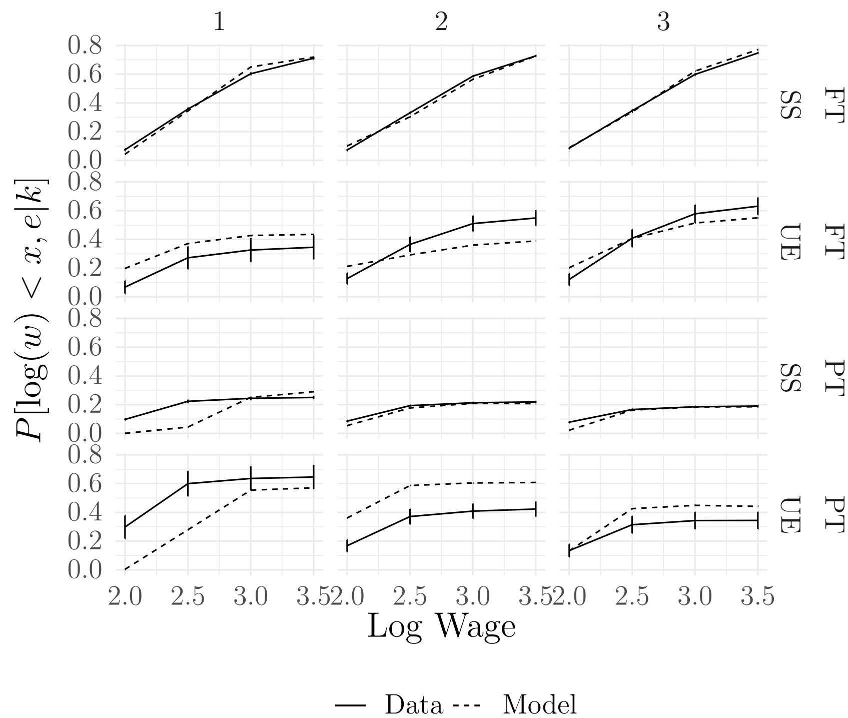
	Data		Model
	Moment	SE of Moment	Moment
County Type 1			
Employment Rate	0.7292	0.0020	0.7192
EE Rate	0.0371	0.0012	0.0405
EU Rate	0.0254	0.0008	0.0254
County Type 2			
Employment Rate	0.7021	0.0013	0.6975
EE Rate	0.0355	0.0008	0.0499
EU Rate	0.0278	0.0008	0.0278
County Type 3			
Employment Rate	0.6560	0.0015	0.6659
EE Rate	0.0321	0.0009	0.0421
EU Rate	0.0306	0.0010	0.0306

This table shows the employment, EE, and EU moments used in the SMM procedure together with the standard errors and the model's fit of these moments.

[19]Naturally these could be properly fit by relaxing the relatively strict parametric assumptions on wages and work costs.

Table 6 reports estimates of the model, with several features of particular interest. First, there is a fair amount of variation in the contact rates among the unemployed and employed, across all county types. Perhaps surprisingly, contact rates among the employed are larger than the contact rates among the unemployed, although the differences are not statistically significant. Second, estimates of ρ indicate that 46% to 64% of job offers correspond to part-time offers, with significant variation across county types. Notice that the fraction of part-time jobs accepted out of unemployment informs this parameter, and that the fraction of the part-time jobs in steady state is smaller. This suggests that appropriate hours arrangements form an important part of the job ladder: workers are willing to accept part-time jobs when unemployed, but gradually shift to full-time jobs when those offers arrive. Third, average offered wages are two times larger for full-time jobs, except for county type 1, where there are no significant differences across hours arrangements. Lastly, women with children have an average cost of work that is more than 1.5 times larger than that of women without children.

Figure 2: SMM Procedure - Auxiliary Wage Moments



This figure shows the wage moments used in the SMM procedure together with the model's fit of these moments. Each data point shows the joint probability of an observed log wage less than or equal to $x \in \{2, 2.5, 3, 3.5\}$ with hours arrangement $e \in \{PT, FT\}$ in either the steady state (SS) or among jobs accepted out of unemployment (UE).

Figure 3 depicts the estimated distribution of firm productivities that rationalizes estimated wage offer distributions, as per Section 4.3. Both part-time and full-time distributions are highly right-skewed, although considerably lower for full-time firms.

Table 5: EE Transition Rates for Women with Children

	Data	Model
County Type 1	0.0241	0.0250
County Type 2	0.0257	0.0277
County Type 3	0.0261	0.0272

This table reports EE transition rates in the data and simulated data using SMM estimates reported in Table 6. These moments are not explicitly targeted in the SMM estimation procedure.

5 Analysis

Having established that adjustments to tax incentives are characterized by hours constraints and search frictions in the labor market, this section uses the quantitative model to ask: what are the implications of this finding for measurement and policy?

The first counterfactual simulates the introduction of the EITC relative to a case without the tax, under the assumption of exogenous wages. This exercises sheds light on the dynamics of responses to the tax and potential differences between short and long-run responses, as well as providing a calculation of the EITC's welfare consequences in the short and long-run.

Since search frictions in many models are consistent with firms having monopsony power (Manning, 2013, 2021), a second counterfactual simulates the introduction of the EITC when wages are set in equilibrium. This allows for a comparison of the positive and normative findings in the first exercise to a setting in which (1) taxes do not, by definition, lead to deadweight loss; (2) wage-setting is endogenous; and (3) market spillovers may contaminate empirical methods that use women without children as a control group.

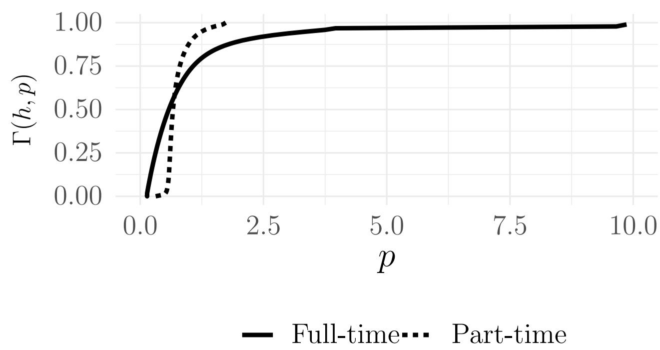
Table 6: SMM Procedure - Model Estimates

	County 1		County 2		County 3	
	Parameter	SE	Parameter	SE	Parameter	SE
ρ_k	0.4645	0.1216	0.6303	0.1200	0.6354	0.1590
$\lambda_{0,k}$	0.1720	0.1409	0.1221	0.1061	0.1478	0.1050
$\lambda_{1,k}$	0.4607	0.3408	0.3671	0.3007	0.3963	0.2674
$\mu_{\alpha,k}$ - no kids	-2.3882	0.9443	-2.6924	1.2307	-2.1245	0.6960
$\mu_{\alpha,k}$ - kids	0.5007	0.7318	0.6337	2.0659	0.7809	1.1710
$\sigma^2_{\alpha,k}$	0.5086	0.3586	2.0376	1.7358	0.2219	0.1522
δ_k	0.0254	0.0008	0.0278	0.0008	0.0306	0.0010
$\mu_{w,1,k}$	-0.1282	0.1435	-0.6162	0.3109	-0.5679	0.3277
$\mu_{w,2,k}$	-0.2744	1.1227	-0.0952	0.7736	-0.1066	0.4797
$\sigma^2_{w,1,k}$	0.0684	0.0524	0.0990	0.0682	0.0645	0.0475
$\sigma^2_{w,2,1}$	0.3278	0.1933	0.6171	0.3335	0.5550	0.3191

This table reports SMM estimates of the model described in Section 3, with three county types. Standard errors are bootstrapped using 100 samples.

The third and final counterfactual considers a marginal expansion in the EITC in partial equilibrium. Once again, the purpose of this exercise is to compare short and long-run consequences of the expansion, with a particular focus on changes in normative policy conclusions based on a sufficient statistic for deadweight loss.

Figure 3: Productivity Distributions



This figure displays the estimated part-time and full-time distribution of firm productivities for county type 3.

5.1 Short and Long-Run Effects of the EITC

In this section, we focus on evaluating tax changes for mothers under full awareness (i.e., county type 3).[20] We therefore ignore the dependence of the transfer function and other parameters on fertility status and awareness. Define the tax function τ as income net of transfers:

$$\tau(w) = w - T(w).$$

Assuming a utilitarian planner, Appendix C shows that welfare in steady state simplifies to the expression:

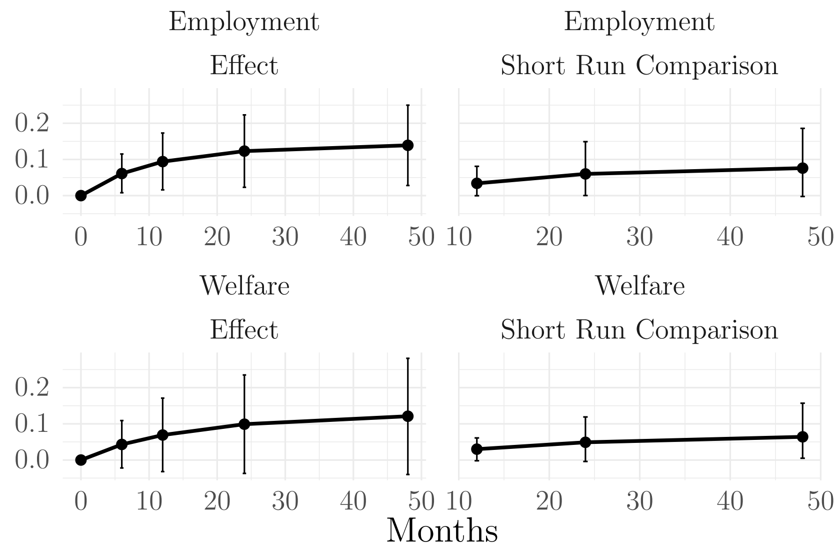
$$W = \int (w - \alpha e) g(x) dx \tag{9}$$

where $x = (w, \alpha, e)$ and g is the density of these variables in steady state.

With equal weights on individuals and linear utility, the cost of transfers is exactly equal to individuals' willingness to pay for them, implying that they do not appear in aggregate welfare.

[20] We concentrate on a scenario of full awareness to avoid confounding effects of changes in taxation with those coming from changes in awareness.

Figure 4: Partial Equilibrium Effects of the EITC



These figures show the effects of the EITC on employment and welfare for single women with children. Clockwise from top left it shows (1) Employment effects of the EITC over time; (2) The difference between the employment effect on a given month and the employment effect at 6 months; (3) The difference between EITC welfare effect calculated on a given month and the EITC welfare effect at 6 months; and (4) Total welfare effects of the EITC. Figures also display the corresponding 95% bootstrap confidence intervals.

The top left panel of Figure 4 depicts the employment effects of the EITC at different time horizons for single women with children. A counterfactual economy in steady state without the EITC provides the comparison with which to estimate the dynamics effects of the tax. Reading from this figure, the estimated model suggests that the long-run effect of the EITC on employment is as high as 14 percentage points. This estimate of the employment effect is higher than that implied by the difference-in-differences estimate of 4 percentage points. This is because the model itself does not exhibit parallel trends, and hence violates the assumptions under which the reduced form estimator uncovers the true effect of the tax.

Figure 4 suggests an additional empirical complication for estimating the effects of the tax, due to the model's dynamics. In the presence of search frictions, workers adjust to the new incentives of the tax by changing their job acceptance decisions, which slows the appearance of employment and earnings effects down to the pace at which workers receive new job offers. The top right panel of 4 offers a comparison of short and long-run effects by depicting the effect of the EITC *relative* to its effect at 6 months after introduction. Point estimates here suggest that employment effects are about 6 percentage points higher after two years relative to the short-run effect, and about 8 percentage points higher in the long-run compared to the short-run. These findings have general implications for empirical designs that rely on short or even medium-run comparisons to estimate tax effects.

In addition to these positive insights, the model has specific normative implications for the effect of the tax. The bottom left panel of Figure 4 calculates the aggregate welfare effects of the tax, which in this version of the model reflect only changes in deadweight loss from taxation. Just as in the competitive setup of Eissa, Kleven and Kreiner (2008*a*), the estimated model suggests that the EITC offsets other distortions and leads to welfare improvements of up to 12% of consumption in the long-run. The bottom left panel also makes short-run welfare calculations that are misspecified in the sense that they are the welfare effects that a researcher would infer if they used these short-run outcomes to compute long-run effects. The bottom right panel depicts the difference of each welfare calculation relative to the one made at 6 months. It shows that the correct long-run welfare effect is about 6 percentage points higher than what could be inferred from effects at 6 months.

5.2 Sufficient Statistics and Marginal Welfare Changes

In order to connect these findings to a broader literature on normative tax policy analysis, this section offers a sufficient statistic for the welfare effects of a marginal tax change and uses it to compare normative inference in the short versus the long-run.

Let the transfer function T be parameterized by some θ. Appendix C shows that, given a set of weights, the change in steady state welfare from a marginal change in the tax function can be written as:

$$\frac{rdW}{d\theta} = \int (1 - \tilde{\mu}(x)) \frac{d\tau(x)}{d\theta} dG(x) + \int \tau(x)\eta(x) dG(x) \tag{10}$$

where once again $x = (w, e, \alpha)$, g is the density of individuals over states x in steady state, and η is its semi-elasticity with respect to the policy change:

$$\eta(x) = g(x)^{-1} \frac{dg(x)}{d\theta}.$$

The first term in equation (10) weighs the marginal benefit to redistribution of the expansion - as measured by the effective planner weight $\tilde{\mu}$ - against the mechanical component of the cost. The second line quantifies the behavioral component of the cost, as unemployment and the distribution of workers over earnings adjusts to the marginal tax change. This expression depends only on reduced form behavioral responses and observable distributions.

Under the simplifying assumption that the planner places equal weights on all individuals, the formula above becomes:

$$\frac{dW}{d\theta} = \int \eta(x) dG(x). \tag{11}$$

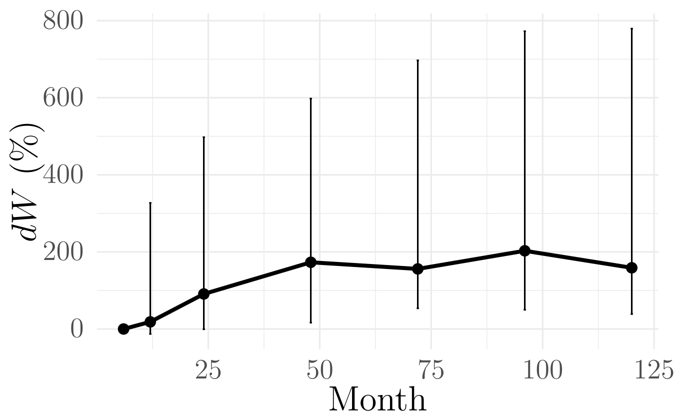
Unlike standard applications of sufficient statistics, this formula does not rely on a small set of elasticities but rather a large number of them. However, it is useful for spelling out the implications of search frictions for any research design that uses short-run marginal policy responses for normative policy conclusions. The counterfactual in this section simulates a marginal expansion[21] in the EITC and compares the welfare calculation suggested by equation (11) at different time horizons.

Figure 5 depicts this marginal welfare calculation using responses up to 10 years after the expansion relative to the short-run calculation at 6 months. Here the results

[21] To be precise: a 10% expansion of the value of the credit at every earnings level.

are very stark. Point estimates suggest that after four years, the *measured* long-run welfare impacts are larger to the order of 200%.

Figure 5: Welfare Effects of a Marginal Expansion of the EITC Relative to The Short-Run Effect



This figure displays the difference between the welfare effect of a marginal expansion of the EITC (i.e., a 10% expansion of the value of the credit at every earnings level) at a given month and its welfare effect at 6 months (i.e., short-run), along with 95% bootstrap confidence intervals.

5.3 Tax Effects with Endogenous Wages

The previous exercises take wages as exogenous when calculating outcomes and welfare. The welfare criterion in equation (9) is valid if wages are equal to marginal output as in Lucas and Prescott (1978). More commonly, search frictions are assumed to lead to firm monopsony power. This section reconsiders the previous counterfactual without the EITC where wages are now set by firms in equilibrium, as in Section 3.5. In contrast to the previous case – in which taxes are only a source of deadweight loss – in this model there is scope for taxes to be welfare improving due to the presence of a market inefficiency. Define welfare in the model as:

$$W = (1 - u) \sum_{e} \int (pe - \alpha e) g(p, e) dw$$

where $g(p, e)$ is the steady state density of workers over firm productivity p and hours arrangement e. This definition follows from equation (9) in the previous section, with firm productivity replacing wages as a measure of total output.

The model also relaxes the strict assumptions on exogeneity of wages. It allows for wage offers to be endogenous to the tax environment as well as opening the possibility of within-market spillovers of the tax to women without children, much like Chetty et al. (2011). Either phenomenon would contaminate estimates of the effect of the tax on employment.

Figure 6: Long-Run Effects of the EITC with Endogenous Wages

These figures compare long-run estimates of the EITC's effects on employment (left panel) and welfare (right panel) under partial and general equilibrium, along with 95% bootstrap confidence intervals for short-run effects.

Figure 6 compares long-run estimates of the EITC's effect on welfare and employment for these opposing assumptions on wage-setting. Encouragingly, it suggests that both the key positive and normative findings of the previous exercise are robust to endogenous wage-posting, mirroring the findings in Shephard (2017).

6 Conclusion

The outcomes of this paper's quantitative exercises suggest that tax policy analysis can be enhanced by considering two deviations from the neoclassical model of labor supply: hours constraints and search frictions. Both components are necessary to make sense of new evidence, and have clear implications for the measurement of positive and normative effects over time, which highlight a stark difference relative to the standard approach. While many alternative model ingredients may also slow adjustment to tax incentives, a key contribution of this paper is to provide direct quantitative discipline for these two in particular. In general, the outcomes of the study emphasise the important role that dynamic models of decision-making have to play for both positive and normative analysis of tax policy reforms.

References

Altonji, Joseph G., and Christina H. Paxson. 1988. "Labor Supply Preferences, Hours Constraints, and Hours-Wage Trade-offs." *Journal of Labor Economics*, 6(2): 254–276.

Bagger, Jesper, Espen R Moen, and Rune Vejlin. 2021. "Equilibrium Worker-Firm Allocations and the Deadweight Losses of Taxation."

Blundell, Richard, Mike Brewer, and Marco Francesconi. 2008. "Job Changes and Hours Changes: Understanding the Path of Labor Supply Adjustment." *Journal of Labor Economics*, 26(3): 421–453.

Bontemps, Christian, Jean-Marc Robin, and Gerard J. Van den Berg. 1999. "An Empirical Equilibrium Job Search Model With Search on the Job and Heterogeneous Workers and Firms." *International Economic Review*, 40(4): 1039–1074.

Burdett, Kenneth, and Dale T Mortensen. 1998. "Wage differentials, employer size, and unemployment." *International Economic Review*, 257–273.

Chetty, Raj. 2012. "Bounds on Elasticities With Optimization Frictions: A Synthesis of Micro and Macro Evidence on Labor Supply." *Econometrica*, 80(3): 969–1018.

Chetty, Raj, J. N. Friedman, and Emmanuel Saez. 2013. "Using Differences in Knowledge Across Neighborhoods to Uncover the Impacts of the EITC on Earnings." *The American Economic Review*, 103(7).

Chetty, Raj, John N. Friedman, Tore Olsen, and Luigi Pistaferri. 2011. "Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records." *The Quarterly Journal of Economics*, 126.

Diamond, Peter A. 1998. "Optimal Income Taxation: An Example with a U-Shaped Pattern of Optimal Marginal Tax Rates." *The American Economic Review*, 88(1): 83–95.

Dickens, William T, and Shelly J Lundberg. 1993. "Hours Restrictions and Labor Supply." *International Economic Review*, 34(1): 169–192.

Eissa, Nada, and Jeffrey B. Liebman. 1996. "Labor Supply Response to the Earned Income Tax Credit." *The Quarterly Journal of Economics*, 111(2): 605–637.

Eissa, Nada, Henrik Jacobsen Kleven, and Claus Kreiner. 2008*a*. "Evaluation of four tax reforms in the United States: Labor supply and welfare effects for single mothers." *Journal of Public Economics*, 92(3-4): 795–816.

Eissa, Nada, Henrik Jacobsen Kleven, and Claus Thustrup Kreiner. 2008*b*. "Evaluation of Four Tax Reforms in the United States: Labor Supply and Welfare Effects for Single Mothers." *Journal of Public Economics*, 92(3-4): 795–816.

Feldstein, Martin. 1999. “Tax Avoidance and the Deadweight Loss of the Income Tax.” *The Review of Economics and Statistics*, 81(4): 674–680.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. 2018. “Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [dataset].”

Grogger, Jeffrey. 2003. “The Effects of Time Limits, the EITC, and Other Policy Changes on Welfare Use, Work, and Income among Female-Headed Families.” *The Review of Economics and Statistics*, 85(2): 394–408.

Harberger, Arnold C. 1964. “The Measurement of Waste.” *The American Economic Review*, 54(3): 58–76.

Hotz, V, and John Karl Scholz. 2006. “Examining the Effect of the Earned Income Tax Credit on the Labor Market Participation of Families on Welfare.” *National Bureau of Economic Research, Inc, NBER Working Papers.*

Kahn, Shulamit, and Kevin Lang. 1991. “The Effect of Hours Constraints on Labor Supply Estimates.” *The Review of Economics and Statistics*, 73(4): 605–611.

Kleven, Henrik K. 2021. “The EITC and the Extensive Margin: A Reappraisal.” Working Paper.

Kreiner, Claus Thustrup, Jakob Roland Munch, and Hans Jørgen Whitta-Jacobsen. 2015. “Taxation and the long run allocation of labor: Theory and Danish evidence.” *Journal of Public Economics*, 127: 74–86.

Lucas, Robert E, and Edward C Prescott. 1978. “Equilibrium search and unemployment.” In *Uncertainty in economics*. 515–540. Elsevier.

Manning, Alan. 2013. “Monopsony in Motion.” In *Monopsony in Motion*. Princeton University Press.

Manning, Alan. 2021. "Monopsony in Labor Markets: A Review." *ILR Review*, 74(1): 3–26.

Meyer, Bruce D. 2010. "The Effects of the Earned Income Tax Credit and Recent Reforms." *Tax Policy and the Economy*, 24(1): 153–180.

Meyer, Bruce D., and Dan T. Rosenbaum. 2001. "Welfare, the Earned Income Tax Credit, and the Labor Supply of Single Mothers*." *The Quarterly Journal of Economics*, 116(3): 1063–1114.

Mirrlees, J. A. 1971. "An Exploration in the Theory of Optimum Income Taxation." *The Review of Economic Studies*, 38(2): 175–208.

Paxson, Christina H., and Nachum Sicherman. 1996. "The Dynamics of Dual Job Holding and Job Mobility." *Journal of Labor Economics*, 14(3): 357–393.

Saez, Emmanuel. 2001. "Using Elasticities to Derive Optimal Income Tax Rates." *The Review of Economic Studies*, 68(1): 205–229.

Shephard, Andrew. 2017. "Equilibrium Search and Tax Credit Reform." *International Economic Review*, 58(4): 1047–1088.

Tazhitdinova, Alisa. 2022. "Increasing Hours Worked: Moonlighting Responses to a Large Tax Reform." *American Economic Journal: Economic Policy*, 14(1): 473–500.

A Evidence of Frictional Adjustment: Regression Analysis and Robustness

Table 7: Regression Evidence on the Effect of the EITC

	Emp	EE	MJH	FT
K	0.008	-0.015	-0.012	0.101
	(0.010)	(0.002)	(0.003)	(0.008)
B	-0.457	-0.035	-0.092	-0.262
	(0.119)	(0.057)	(0.048)	(0.176)
$K \times B$	0.293	0.048	0.088	-0.018
	(0.090)	(0.015)	(0.022)	(0.056)
Num.Obs.	435,633	194,297	429,666	281,485
R^2	0.078	0.005	0.020	0.087
Educ.	X	X	X	X
County	X	X	X	X
Date	X	X	X	X

This table reports estimates of the regression equation (4) for four outcomes: employment (Emp); employer-employer transitions (EE); multiple job holding (MJH); and full-time employment (FT). MJH is a monthly indicator for employed individuals and is equal to one if respondents report holding two or more jobs simultaneously. Individuals are said to be working full-time if they report 30 or more usual weekly work hours. Standard errors are displayed in parenthesis.

Table 8: Robustness Test: Placebo Treatment

	Emp	EE	MJH	FT
K	0.017	-0.015	-0.010	0.106
	(0.010)	(0.002)	(0.003)	(0.008)
B	-0.460	-0.035	-0.092	-0.262
	(0.119)	(0.057)	(0.048)	(0.176)
$K \times B$	0.281	0.050	0.076	-0.040
	(0.086)	(0.017)	(0.023)	(0.059)
K_3	-0.053	0.001	-0.010	-0.029
	(0.014)	(0.004)	(0.005)	(0.012)
$K_3 \times B$	0.112	-0.011	0.059	0.138
	(0.098)	(0.031)	(0.037)	(0.089)
Num.Obs.	435,633	194,297	429,666	281,485
R^2	0.078	0.005	0.020	0.087
Educ.	X	X	X	X
County	X	X	X	X
Date	X	X	X	X

This table reports estimates of the regression equation (7) for four outcomes: employment (Emp); employer-employer transitions (EE); multiple job holding (MJH); and full-time employment (FT). MJH is a monthly indicator for employed individuals and is equal to one if respondents report holding two or more jobs simultaneously. Individuals are said to be working full-time if they report 30 or more usual weekly work hours. Standard errors are displayed in parenthesis.

B Identification of the Model

In what follows, recall that $u(\alpha)$ is the steady state fraction of workers of type α who are unemployed. For women without children, it is given by:

$$u(\alpha) = \frac{\delta}{\delta + \lambda_0 \tilde{F}_{Z|\alpha}(z^*_\alpha)}.$$

B.1 Identification of offer distributions, f_W

Consider the distribution of accepted wages given a transition between two jobs with the same hours arrangement, e. Call this distribution G_{ee}. In this case, all jobs that offer a higher wage are accepted, giving:

$$G_{ee}(w) \propto \int^{w} G_W(x,e) f_W(x,e) dw$$

and density:

$$g_{ee}(w) \propto G_W(w,e) f_W(w,e) dw.$$

Given that the steady state distributions $(G_W(\cdot,1), G_W(\cdot,1))$ are identified by a single observed cross-section of hours and wages, both offer distributions are known up to a constant of proportionality, c, that determines the relative frequency of full time and part time offers:

$$f_W(w,1) = c f^*_W(w,1) \tag{12}$$

$$f_W(w,2) = (1-c) f^*_W(w,2) \tag{13}$$

$$\int f^*_W(w,e) dw = 1 \tag{14}$$

Now, define the distribution (A_0, A_1) to be the pair of distributions of reservation wages. We can define these as:

$$A_e(w) \propto \int \mathbf{1}\{z^*_\alpha + \alpha e \leq w\} u(\alpha) dH(\alpha|0).$$

These distributions can be used to define the conditional distribution of part-time and full-time wages accepted out of unemployment:

$$g_{0e|e}(w) = \frac{A_e(w) f_W(w,e)}{\int A_e(x) f_W(x,e)} = \frac{A_e(w) f^*_W(w,e)}{\int A_e(x) f^*_W(x,e)}.$$

Since each f^*_W is known, each A_e is identified from the above equation. Letting π_{01} be the fraction of part-time jobs accepted out of unemployment, we can write this as:

$$\pi_{01} = \frac{\kappa \int A_1(w) f^*_W(w,1) dw}{c \int A_1(w) f^*_W(w,1) dw + (1-c) \int A_2(w) f^*_W(w,2) dw}$$

and hence the relative frequency of part-time offers, c is identified.

B.2 Identification of λ_0

The steady steady flow from unemployment to employment is:

$$UE = \lambda_0 \left(\int A_1(w) f_W(w,1) dw + \int A_2(w) f_W(w,2) dw \right).$$

Since the term in brackets is identified and the left hand side is known, λ_0 is identified.

B.3 Identification of δ,ζ, and λ_1

δ is identified by the flow rate of workers from employment to unemployment, while ζ is assumed to be known. Let $EE(e)$ be the steady state flow of workers between jobs *within* an hours arrangement, e. This is equal to:

$$EE(e) = \lambda_1 \int g_{W|e}(w|e) \tilde{F}_W(w,e)$$

where $g_{W|e}$ is once again identified by a single cross-section of hours and employment and the offer distribution F is identified by a previous step. Since each term in the integral is identified, λ_1 is identified as well.

B.4 Identification of H

Finally, returning to the expression for reservation utilities, the mapping to derive reservation utility, z^*_α, is known. Hence, either of the distributions A_e can be used to invert H as follows:

$$h(\alpha|1) = \frac{a_e(z^*_\alpha + \alpha)/u(\alpha)}{\int a_e(z^*_x + x)/u(x) dx}$$

where $u(\alpha)$ is given as above.

C Welfare and Sufficient Statistics

Let $x = (w, e, \alpha)$ summarize an individual's relevant state variables, such that $u(x) = T(w) - \alpha e$. Since the paper only considers welfare calculations for women with children in the case of full awareness, the expressions here ignore dependence on these state variables. Define the tax function $\tau(x) = w - T(w)$. Let $\lambda_t(x|x_0)$ be the conditional density over future states x at time t induced by an agent who is initially in state x_0 and is making optimal decisions. Let $V(x_0)$ be the resulting expected discounted present value of an agent in state x_0. Assuming that the planner has weights μ over $\mathcal{X} = \{0, 1, 2\} \times \mathbb{R}_+^2$, the planner's objective is:

$$W = \int \mu(x)V(x)dG_0(x) + \int e^{-rt}\tau(x)dG_t(x)dt.$$

Here the assumption is that tax revenue at time t (the second term) is either rebated lump sum to all agents or valued by the planner for some other use (in which case the scale of μ indicates overall tastes for redistribution). Substituting in the definition of V, this objective is equivalently:

$$W = \int \mu(x_0)e^{-rt}Z(x)\lambda_t(x|x_0)dtdG_0(x_0) + \int e^{-rt}\tau(x)dG_t(x)dt$$

where $Z(x)$ is the worker's flow utility in state x. Now assume that τ is indexed by a finite set of parameters θ and consider a marginal expansion in the tax code. Since λ_t is optimally chosen by each agent to maximize discounted present values, an envelope theorem applies, giving the expression:

$$\frac{dW}{d\theta} = -\int \mu(x)e^{-rt}\frac{d\tau(x_t)}{d\theta}\lambda_t(x_t|x)dx_t dtdG_0(x) + \int e^{-rt}\left(\frac{d\tau(x)}{d\theta} + \tau(x)\eta_t(x)\right)dG_t(x)dt$$

where $\eta_t(x) = g_t(x)^{-1}dg_t(x)/d\theta$ is the *semi-elasticity* of the density g_t with respect to the policy change. Since $g_t(x) = \int \lambda_t(x|x_0)dG_0(x_0)$, the expression simplifies to:

$$\frac{dW}{d\theta} = \int e^{-rt}\left[\frac{d\tau(x)}{d\theta}(1 - \tilde{\mu}_t(x)) + \tau(x)\eta_t(x)\right]dG_t(x)dt$$

where $\tilde{\mu}_t(x) = g_t(x)^{-1}\int \mu(x_0)\lambda_t(x|x_0)dG_0(x_0)$ is the "effective" planner weight on agents in state x at time t. This is a sufficient statistic for welfare gains in the sense that the first term requires only data on welfare weights and current distributions, while the second term requires in addition only the reduced form behavioral parameters η_t.

Supposing that one is only interested in steady state welfare comparisons, the formula above simplifies because $\tilde{\mu}_t$ and g_t are constant over time, giving equation (10) in the main text:

$$\frac{rdW}{d\theta} = \int (1 - \tilde{\mu}(x)) \frac{d\tau(x)}{d\theta} dG(x) + \int \tau(x)\eta(x)dG(x).$$

Further assuming a utilitarian planner ($\mu(x) = 1$), the expression for welfare becomes

$$rW = \int (w - \alpha e)dG(x)$$

and the marginal change in welfare simplifies to:

$$\frac{rdW}{d\theta} = \int \tau(x)\eta(x)dG(x) = \int (w - \alpha e)\frac{dg(x)}{d\theta}dx.$$

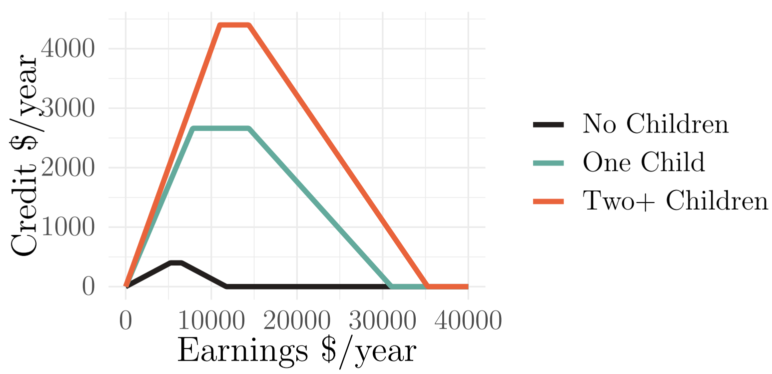
as found in (9) and (11).

D EITC Structure

The Earned Income Tax Credit (EITC) provides a subsidy to families in which at least one member works. The total amount of the EITC depends on income and the number of children. Qualifying children are resident children younger than 19 years old or permanently disabled.

Figure 7 shows the credit amount as a function of earned income and number of qualifying children, as of year 2005. The credit first increases linearly with earnings in the phase-in region, then plateaus over a given income range, and then decreases linearly in the phase-out region. In 2005, the phase-in credit rate was 34% for individuals with one child and 40% for individuals with two or more children; the corresponding phase-out rates were 15.98% and 21.06%. Families with resident children are bound to receive a significant credit. The maximum credit was \$2,662 and \$4,400 for taxpayers with one child, and two or more children, respectively. Individuals with no children only received a small credit, with a 7.65% phase-in rate and a maximum credit of \$399. The credit clearly targets families with low to moderate income: the maximum income to receive the credit was \$31,030 and \$35,263 for taxpayers with one child, and two or more children, respectively.

Figure 7: EITC Schedule - Year 2005



This figure depicts the EITC credit schedule for single filers with no children, one and two or more children, in 2005.

E Model Solution

E.1 Reservation Utilities

Recall that $F_{Z|\alpha}(z)$ is the effective distribution of job flow utilities induced by the joint wage and hours offer distributions $F_W(\cdot, e)$. Dependence on f and a is suppressed for simplicity. Let U_α denote the value of unemployment for a worker of type α and let $V_\alpha(z)$ be the value of employment at a firm offering flow utility z. These values take the recursive representation:

$$(r+\zeta f)U_\alpha = T(0,a,f) + \lambda_0 \int \max\{0, V_\alpha(z) - U_\alpha\} dF_{Z|\alpha}(z) \quad (15)$$

$$(r+\zeta f)V_\alpha(z) = z + \lambda_1 \int \max\{0, V_\alpha(z') - V_\alpha(z)\} dF_{Z|\alpha}(z') + \delta(U_\alpha - V_\alpha(z)). \quad (16)$$

The optimal strategy for employed workers is to simply accept jobs that offer a higher flow utility. Thus, it can be shown that:

$$V'_\alpha(z) = \frac{1}{r + \zeta f + \delta + \lambda_1 \tilde{F}_{Z|\alpha}(z)} \quad (17)$$

where $\tilde{F} = 1 - F$ for any distribution. Since V_α is strictly increasing in z, unemployed workers' optimal job acceptance decision is characterized by their reservation utility, defined as the job offer that leaves them indifferent between work and unemployment:

$$V_\alpha(z^*_\alpha) = U_\alpha.$$

Applying this definition, and using integration by parts with (17) yields the implicit solution for z^*_α as in the main text:

$$z^*_\alpha = T(0,a,f) + (\lambda_0 - \lambda_1) \int_{z^*_\alpha} \frac{\tilde{F}_{Z|\alpha}(z)}{r + \zeta f + \delta + \lambda_1 \tilde{F}_{Z|\alpha}(z)} dz.$$

E.2 Characterizing Steady State

First consider women of type α without children (whose flows are slightly less complicated since there is no awareness process). Their unemployment rate

$$u(\alpha) = \frac{\delta}{\delta + \lambda_0 \tilde{F}_{Z|\alpha}(z^*_\alpha)}$$

balances the flows out of employment ($\delta(1 - u(\alpha))$) with flows in ($u(\alpha)\lambda_0 \tilde{F}_{Z|\alpha}(z^*_\alpha)$). Similarly, the distribution of employed workers over utility levels:

$$G_{Z|\alpha}(z) = \frac{F_{Z|\alpha}(z) - F_{Z|\alpha}(z^*_\alpha)}{1 + \kappa \tilde{F}_{Z|\alpha}(z)}$$

balances flows in $(u(\alpha)\lambda_0(F_{Z|\alpha}(z)-F_{Z|\alpha}(z^*_\alpha)))$ with flows out $((1-u(\alpha))(\delta+\lambda_1\tilde{F}_{Z|\alpha}(z))$ where $\kappa = \lambda_1/\delta$. Similarly, if one defines the joint distribution over utilities and employment offers as:

$$F_{Z|\alpha}(z,e) = F_W(T^{-1}(z+\alpha e, a, f), e)$$

then this leads to a derivation of the steady state joint density of workers over utilities and employment arrangements:

$$g_{Z|\alpha}(z,e) = \frac{f_{Z|\alpha}(z,e)}{\tilde{F}_{Z|\alpha}(z^*_\alpha)} \frac{1+\kappa\tilde{F}_{Z|\alpha}(z^*_\alpha)}{(1+\kappa\tilde{F}_{Z|\alpha}(z))^2}$$

by balancing:

$$\underbrace{f_{Z|\alpha}(z,e)[\lambda_0 u(\alpha)+\lambda_1(1-u(\alpha))G_{Z|\alpha}(z)]}_{\text{flows in}} = \underbrace{g_{Z|\alpha}(z,e)[\delta+\lambda_1\tilde{G}_{Z|\alpha}(z,e)]}_{\text{flows out}}.$$

With this in hand, it is simple enough to back out the implied steady state density over earnings and hours arrangements using a change of variables:

$$g_{W|\alpha}(w,e) = T'(w)g_{Z|\alpha}(T(w)-\alpha e, e)$$

which can be calculated for all points at which the transfer function T is differentiable.

Women with children are slightly more complicated to characterize in this economy due to their additional flows between awareness states and exits from the economy. Let π_a be the steady state fraction of workers who are aware of the tax. Balancing flows gives:

$$\pi_a = \frac{\xi}{\xi+\zeta}.$$

Letting $u_a(\alpha)$ be the fraction of workers with awareness status a that are unemployed. The steady state fraction that balances flows out (new hires) with flows in (exits and newly eligible individuals) is:

$$u_0(\alpha) = \frac{\delta+\zeta+\xi}{\lambda_0\tilde{F}_{Z|\alpha,0}(z^*_{\alpha,0})+\xi+\delta+\zeta}, \qquad u_1(\alpha) = \frac{\delta+\zeta u_0(\alpha)}{\lambda_0\tilde{F}_{Z|\alpha,1}(z^*_{\alpha,1})+\zeta+\delta}.$$

Following the same approach as for the case of women without children, the distribution over utilities for unaware workers, $G_{Z|\alpha,0}$, is:

$$G_{Z|\alpha,0}(z) = \frac{u_0(\alpha)\lambda_0(F_{Z|\alpha,0}(z) - F_{Z|\alpha,0}(z^*_{\alpha,0}))}{(1-u_0(\alpha))(\xi+\delta+\zeta+\lambda_1\tilde{F}_{Z|\alpha,0}(z))}.$$

Defining $k = \frac{\lambda_1}{\delta+\zeta+\xi} < \kappa$, this expression simplifies to:

$$G_{Z|\alpha,0}(z) = \frac{(F_{Z|\alpha,0}(z) - F_{Z|\alpha,0}(z^*_{\alpha,0}))}{\tilde{F}_{Z|\alpha,0}(z^*_{\alpha,0})(1+k\tilde{F}_{Z|\alpha,0}(z))}$$

where $k = \frac{\lambda_1}{\delta+\zeta+\xi} < \kappa$. Now consider a worker receiving utilty z with hours e. When they become aware of the tax, their new utility z' is:

$$z' = T(T{-}1(z+\alpha e, 0, 1), 1, 1) - \alpha e.$$

Similarly, the inverse of this mapping is:

$$z = T(T{-}1(z'+\alpha e, 1, 1), 0, 1) - \alpha e = \varphi(z', e).$$

Conditional on employment, e, this mapping is monotonic, and hence the flow of newly aware workers with new utility less than or equal to z is:

$$(1-\pi_a)(1-u_0(\alpha))\xi\left(G_{Z|\alpha,0}(\varphi(z,1),1) + G_{Z|\alpha,0}(\varphi(z,2),2)\right).$$

With this flow rate characterized, the steady state distribution over utilities for aware workers must be:

$$G_{Z|\alpha,1}(z) = \frac{u_1(\alpha)\lambda_0(F_{Z|\alpha,1}(z) - F_{Z|\alpha,1}(z^*_{\alpha,1})) + \zeta(1-u_0(\alpha))\left(G_{Z|\alpha,0}(\varphi(z,1),1) + G_{Z|\alpha,0}(\varphi(z,2),2)\right)}{(1-u_1(\alpha))(\delta+\zeta+\lambda_1\tilde{F}_{Z|\alpha,1}(z))}$$

and the density of workers at each utility level z and hours arrangement e is:

$$g_{Z|\alpha,1}(z,e) = \frac{f_{Z|\alpha,0}(z)(u_0(\alpha)\lambda_0 + (1-u_0(\alpha))\lambda_1 G_{Z|\alpha,1}(z)) + \zeta(1-u_0(\alpha))g_{Z|\alpha,0}(\varphi(z,e))}{(1-u_1(\alpha))(\delta+\zeta+\lambda_1\tilde{F}_{Z|\alpha,1}(z))}.$$

As before, the relationship:

$$Z = T(w, a, 1) - \alpha e$$

can be used to calculate the density of workers over wages and employment states using a change of variables. Calling these $g_{W|\alpha,a}$, the unconditional densities are therefore:

$$g_W(w,e) \propto \int \left((1-\pi_a)g_{W|\alpha,0}(w,e)(1-u_0(\alpha)) + \pi_a g_{W|\alpha,1}(w,e)(1-u_1(\alpha))\right) dH(\alpha,1).$$