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

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Abstract

This paper finds that single mothers respond to the Earned Income Tax Credit (EITC) - an employment subsidy - by switching jobs more frequently, accepting lower wage positions, and by accepting more part-time jobs when unemployed. A labor market model with hours constraints and search frictions can rationalize these findings, and brings additional empirical and policy implications relative to the standard neoclassical benchmark. When matching the evidence, the model indicates substantial differences between the short and long-run responses of single mothers to the EITC. The long-run effect on employment, for example, is about 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 present a stark comparison to the commonly used frictionless model, and emphasise the important role played by dynamic frictions for tax policy analysis.

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1 Introduction

The neoclassical model of labor supply is a workhorse tool for tax policy analysis. Under the assumption 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 first documents new margins of response to the Earned Income Tax Credit (EITC) that are not articulated (and hence cannot be explained) in the standard neoclassical model. It then estimates a dynamic model of on-the-job search with hours constraints – two departures from the frictionless model that can rationalize this new evidence – drawing out additional positive and normative implications from the model. A key insight is that there are meaningful differences between short and long-run responses to the tax changes.

An empirical design borrowed from Chetty, Friedman and Saez (2013) provides evidence that the EITC,[1] in addition to its well-documented effects on employment, also affects the rate at which single mothers switch jobs, and on the types of jobs that they are willing to accept. 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 of the EITC schedule. Chetty, Friedman and Saez (2013) comprehensively validate this measure as a proxy for local 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 applies this assumption to derive 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

[1] 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.

and low awareness counties yields estimates of the EITC's effects, indicating increases in employment, higher monthly employer-employer (EE) transition rates, and a greater 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, these kinds of responses are not articulated in the standard neoclassical model, where workers are frictionless and immediately assigned to jobs.

The next stage of the analysis introduces a labor market model with two key frictions to match the evidence.[2] First, jobs are characterized by a wage and a fixed number of hours that cannot be adjusted in response to changes in incentives (Altonji and Paxson, 1988; Chetty et al., 2011). 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. 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 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. In accordance with the first stage empirical analysis, the model assumes that awareness is an exogenous stochastic process.

The DD and structural approaches provide two alternative sets of (ultimately untestable) assumptions for forecasting counterfactual outcomes, and therefore for inferring the causal

[2] 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.

effects of the EITC. While the DD strategy requires parallel trends between individuals with and without children across county types, the model imposes a deeper structural mapping between model primitives and observed wages, hours, and job transitions. The model is non-parametrically identified from a single cross-section of these variables and provides a forecast of any tax reform counterfactual given those primitives. Importantly, there is no guarantee that parallel trends should hold for the estimated model, and hence the two approaches need not yield identical estimates even when fitting the observed data equally well. 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. The model estimates larger impacts on employment and EE transitions, but in both cases these differences can be accounted for either by statistical noise, or by potential discrepancies between long and short-run effects.

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 13-14 percentage point increase in employment for single mothers in the long-run, a full 7-8 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 – defined as the reduction in deadweight loss from taxation – is a gain of 11.5% relative to the baseline. 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 a 5% reduction in deadweight loss, less than half the true effect. To further unpack the result, a second counterfactual studies an additional marginal expansion in the EITC and applies a sufficient statistic formula to calculate the welfare impact. 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.

An additional set of counterfactuals assesses the relative importance of search frictions and hours constraints for these quantitative results, finding that each play an important role and interact in non-trivial ways. The counterfactuals alternatively compute the EITC's impacts on employment and EE transitions when each friction is neutralized. The first scenario removes hours frictions by allowing workers to choose whatever hours arrangement maximizes their utility, given the hourly wage on offer. The model exhibits identical effects on EE transitions compared to the baseline, and a modest reduction in employment effects. The second counterfactual aims to reduce search frictions by scaling up contact rates, first by 50% and then by 100%. As a result, the impact on EE rates is eliminated almost entirely, and the effect on employment declines by up to 10 percentage points.

The results suggest a number of conclusions. First, search frictions are chiefly responsible for the observed impacts on EE rates, and hours constraints play a limited role. As later sections of the paper will make clear, the EITC lowers reservation wages for all hours arrangements. This "lengthens" the job ladder, resulting in a greater fraction of employed workers finding preferable jobs in steady state. This effect, and its magnitude, persist regardless of whether hours arrangements are completely flexible or completely inflexible. Employment effects operate through this same reduction in reservation wages, a behavioral response that becomes more muted as search frictions disappear. In contrast however to EE rates, constraints on hours interact with search frictions to have meaningful impacts on quantities. The EITC makes some part-time jobs more acceptable by subsidizing wages, and workers respond by accepting more of them, which contributes to the rise in employment. The empirical evidence, which also documents an increase in the fraction of part-time jobs accepted out of unemployment, validates this particular mechanism. Hence, search frictions and hours constraints interact in a way that magnifies the EITC's effect on employment.

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).[3] 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 (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.

This paper makes three main contributions. First, it provides novel empirical evidence on margins of adjustment to the EITC that have not been documented in prior work: job-to-job transition rates, the distribution of wages for jobs accepted out of unemployment, and the types of hours arrangements workers accept. The latter two sets of findings, which focus on transitions out of unemployment, are unique to the study of tax incentives more generally. Second, the paper develops a quantitative framework that isolates the separate roles of hours constraints and search frictions through counterfactual exercises that neutralize each friction, finding that search frictions are primarily responsible for increased job-switching

[3] 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.

while interactions between the two frictions amplify employment effects. Third, and most importantly for policy, it demonstrates that the distinction between short and long-run effects can be quantitatively large: welfare effects measured using long-run responses are more than double those measured using short-run responses, highlighting the importance of accounting for adjustment dynamics in frictional labor markets.

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 derives a sufficient statistic for the welfare impacts of a marginal change to the EITC schedule. Section 6 performs counterfactuals that depict the implications of hours constraints and search frictions in the labor market for policy analysis and measurement. Lastly, Section 7 offers concluding thoughts.

2 Evidence of Frictional Adjustment to the EITC

2.1 Empirical Strategy and Identification

This section describes the empirical strategy used to examine the response of single mothers in the United States to the EITC.[4] The empirical analysis is built around the following model of outcomes for individual i in county $c(i)$:

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

where Y_i is the outcome of interest for individual i, $F_i \in \{0, 1\}$ 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 of individuals who are aware of the tax in county $c(i)$. Conditioning out A_i gives:

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

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

The model specifies that while outcomes may vary systematically across counties, differences between eligible ($F = 1$) and ineligible ($F = 0$) 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 measure, B_{ct}. For now, one should simply assume that such a measure exists. Section 2.2.2 will later describe this measure in more detail. Assume that measurement 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 $\pi_{ct} = \pi_{k(c)}$. The stationarity assumption ensures a consistent interpretation of the data with respect to the upcoming model, which requires that the economy is in steady state.

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 $\pi_1 < \pi_2 < ... < \pi_K = 1$.

Identification of the causal parameter γ follows from the usual difference-in-differences logic. Consider a comparison between the lowest awareness county type and the full awareness county type. Notice that (2) implies

$$\gamma = \frac{(\mathbb{E}[Y|k = K, F = 1] - \mathbb{E}[Y|k = K, F = 0]) - (\mathbb{E}[Y|k = 1, F = 1] - \mathbb{E}[Y|k = 1, F = 0])}{1 - \pi_1} \tag{4}$$

which motivates this paper's preferred estimation approach: a simple DD estimator constructed from estimates of the individual moments above. In words, γ is identified by examining how the difference in outcomes between individuals with children and those without evolves when comparing the lowest awareness counties to counties with full awareness. Under the assumption that those differences are stable in the absence of the tax (parallel trends), the difference-in-differences is attributable to the effect of the tax. Appendix A considers a more complete set of moment conditions and demonstrates that estimates are robust to an estimation strategy that employs all such identifying information.

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.[5] Information on earnings and wages is also available for a subset of 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. In the previous literature on the effects of the EITC, single mothers have received an overwhelming share of the focus, which motivates their selection here as the main sample of interest. Appendix A repeats the analysis for additional subgroups.

2.2.2 Sharp Bunching Measure

Chetty, Friedman and Saez (2013) argue comprehensively that local awareness of the EITC can be measured by an *excess or sharp bunching* measure: the percentage of EITC claimants with children who report total earnings within $500 of the first kink of the EITC schedule (which maximizes the tax refund) and have non-zero self-employment income. Self employment income, as compared to wage income, is self-reported and comparatively much easier

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

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.

to manipulate in order to maximize tax refunds. Of course, individuals only have an incentive to do this if they are aware of the tax, and hence the preponderence of this behavior represents a proxy for local awareness in each location. Appendix F provides a more detailed discussion of the measure, and describes a number of the validation steps employed by Chetty, Friedman and Saez (2013) to argue that the measure is a good proxy for local awareness among wage earners.

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[6] 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. Crucially, the finite mixture model estimation procedure explicitly accounts for measurement error in the bunching proxy through the additive error term ϵ_{ct} in equation (3), the distribution of which is estimated jointly with the awareness parameters. This ensures that any measurement error arising from the county-level aggregation does not bias the estimated tax effects; moreover, classical measurement error can only attenuate effects toward zero through attenuation bias, not create spurious findings.

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

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.

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 maximum likelihood 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.

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

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

For any outcome Y_i, where i indexes observational units, moments can be estimated for each county type[7] as:

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

Then, following equation (4), the expression

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

delivers an estimate of the effect γ of the tax on each outcome Y.

The next section documents estimates for the outcomes of interest using the approach outlined in equation (6).

2.4 Results

2.4.1 Results on Employment, Hours, and Transitions

Table 3 reports estimates of the tax's effects on six outcomes of interest, following the estimation approach outlined in Section 2.3. These six outcomes are (1) average employment; (2) the rate at which employed individuals make employer-employer (EE) transitions; (3) the rate at which employed individuals make transitions to unemployment (EU); (4) the fraction of employed individuals working full-time (FT) hours; (5) the fraction of jobs with full-time hours accepted by unemployed individuals (FT given UE); and (6) the fraction of employed individuals with more than one job (multiple job-holding, MJH).

Prior work suggests that responses to the EITC overwhelmingly operate at the extensive margin, and hence it is crucial to discipline the structural model with estimated employment effects. Furthermore, replicating the results of Chetty, Friedman and Saez (2013) by finding positive employment effects will serve to validate this paper's estimation approach. Outcomes (2) through (6) are of particular interest because of their potential relationship to the frictions introduced by the upcoming quantitative model. If workers face hours constraints, they may satisfy their desire to work more or less in response to an earnings subsidy by their job search

[7] Since the outcomes Y are not included in the calculated posterior weight, there is potential for bias in this estimator of the conditional moment if posteriors are noisy. However since 95% of the posterior weights lie below 0.05 or above 0.95, bias is not a concern here.

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

Outcome	Estimate	95% Conf. Interval
Employment	0.042	[0.006 0.091]
Employer-employer transitions	0.011	[0.004 0.021]
Employment-unemployment transitions	-0.002	[-0.008 0.004]
Full-time hours	-0.021	[-0.058 0.015]
Full-time hours accepted out of unemployment	-0.236	[-0.451 -0.036]
Multiple-job-holding	0.019	[0.006 0.032]

This table reports estimates using equation (6), where moments are calculated using estimates from the finite mixture model using (5). Confidence intervals are calculated via county-level bootstrap with 200 replacement samples.

strategies[8] (resulting in an increase in EE transitions) or by taking second jobs (Paxson and Sicherman, 1996). Unemployed workers who face uncertain future job opportunities will be willing to accept lower wage jobs and jobs with previously unacceptable hours arrangements. [9]

Table 3 reports estimated effects on each outcome with 95% confidence intervals. 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 even a standard perfectly competitive model, the second requires a richer framework where EE transitions can be rationalized and are responsive to policy. Turning to hours, results indicate that while there is no statistically detectable effect on full-time employment in the cross-section, there is a significant reduction (20 percentage points) in full-time hours among jobs accepted by workers out of unemployment. This is potentially indicative of constraints on hours since one would expect that, if hours were completely flexible, the impacts should be similar for newly employed workers compared to workers in the cross-section. As it stands, results indicate that workers may be more willing, in response to the tax, to accept part-time

[8] Section 3.3 will demonstrate that the EE rate is likely to rise even in the absence of hours constraints.

[9] The very next section will present evidence on this particular response channel.

hours arrangements when unemployed.

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. Furthermore, the omission of MJH from the model does not appear to have any obvious implications for the main contribution of the model, which is to compare the short and long-run responses to the tax and make welfare calculations based on earnings elasticities across the distribution.

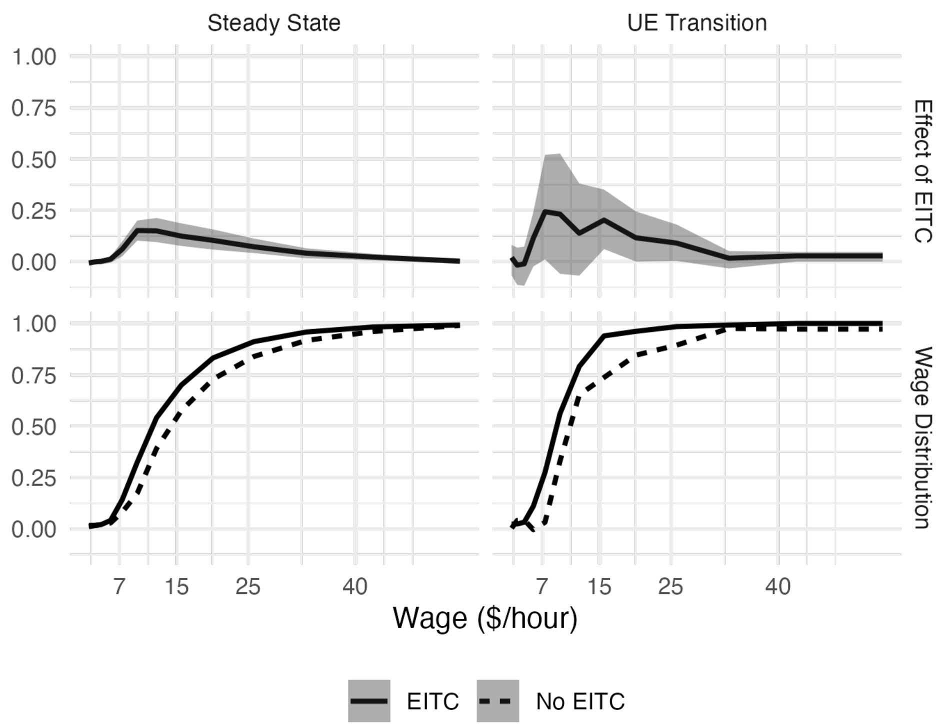
2.4.2 Results on the Wage Distribution

While employment and job-to-job transitions are the primary outcomes of interest, the upcoming model also has implications for the effect of the EITC on wages. In particular, workers should be willing to accept lower wage jobs out of unemployment, regardless of hours, with potential spillover effects to the distribution of wages in steady state. Accordingly, Figure 1 presents difference-in-differences estimates of the effect of the tax on the cumulative distribution (CDF) of wages. The top left panel shows estimated effects for the entire cross-section (interpreted by the model as the steady state distribution), while the top right panel shows estimates for for jobs newly accepted in a transition out of unemployment (UE). To assist with the interpretation of these effects, the bottom left and right panels of the figure use these effects to compare the CDF of log wages under the tax (the observed distribution) to the counterfactual distribution without the EITC (equal to the obsered distribution minus estimated effects).

Figure 1 suggests that the EITC has shifted the distribution of log-wages to the left, with effects on the wage distribution appearing for wages as low as $7 an hour. The effect appears in both the "steady state" as well as jobs accepted out of unemployment (a UE transition). Although imprecise, point estimates of this effect are larger and occur at lower wages for wages accompanied by a UE transition.

The upcoming quantitative model is equipped to interpret these facts through individ-

Figure 1: Difference-in-Differences Estimates of Tax Effects on Wage Distributions



This figure depicts estimates, using equation (6), of the effect of the EITC on the distribution of log-wages, with the x-axis transformed to reflect wage levels. The top-left panel shows estimates of the effect on the cross-sectional or "steady state" (SS) distribution. The top-right panel shows effects on the distribution for jobs accepted out of unemployment. The bottom-left and bottom-right panels compare those same wage distributions in full-awareness counties ("EITC") to the counterfactual of "No EITC", which is calculated by deducting estimated effects. Ribbons indicate a 95% bootstrapped confidence interval from 200 county-level replacement samples.

uals' job acceptance decisions. Since the EITC subsidizes earnings, it makes all jobs more attractive relative to unemployment, and lowers the reservation wage for both full and part-time job offers. Since workers can only achieve higher wages by finding new jobs, this initial effect on wages accepted out of unemployment has a persistent effect on the distribution in steady state.

2.5 Sub-group Analysis and Robustness

While this paper focuses chiefly on the EITC's effects on single mothers, it is natural to consider whether there are broader impacts across other demographic groups. Figure 9 in Appendix A presents difference-in-difference estimates across groups divided by education, sex, and marital status. These estimates additionally split the results for single mothers into a group with at most a high school diploma or equivalent ($\leq HS$) and a group with at least some post-secondary education ($> HS$). This analysis does not produce any clear patterns of interest. In particular, there do not appear to be statistically detectable differences between the estimates for low and high educated single mothers. With the caveat that the exercise is implicitly subject to multiple hypothesis testing issues, one might potentially conclude that higher educated single fathers exhibit similar impacts to single mothers, and that the tax may have had a positive impact on the full-time employment of married mothers.

As a further robustness test, Figure 9 in Appendix A presents alternative estimates of the tax effects that makes use of the additional identifying information from counties of type $k = 2$. Equation (2) suggests that the effect of the tax γ can also be identified by projecting variation in awareness on outcomes with county type fixed effects. Figure 9 also presents estimates based on such a regression, with posterior weights used for each county type. Results are generally robust to this alternative estimation strategy.

Appendix A also presents the results of a regression-based approach that more closely mirrors the design of Chetty, Friedman and Saez (2013). Table 7 presents the estimates from a regression with additional county, time, and education 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 women with three or more children as a new potential treatment group. For the analysis period in this paper, having three or more children did not additionally change tax credit entitlements relative to having two children.[10] 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 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.

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.[11] 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

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

[11] 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.

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 ($a \in \{0, 1\}$). 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.

Individuals receive job offers at a constant poisson rate that depends on their employment status, $\lambda_{e,k}$. 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. Thus, $\rho_k = \lim_{w\to\infty} F_{W|k}(w, 1)$ is the probability that a job offer has part-time hours.[12] 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

[12] This setup is equivalent to allowing part- and full-time jobs to have different offer arrival rates.

type, k. In the model, workers care only about the flow utility of each job, and so it is 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, $(\lambda_0 - \lambda_1)$. 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[13], 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

[13]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.

jobs, resulting in an increase in employment.[14]

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 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.

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

3.5 Endogenous Wages

The assumption that wages are competitively set and exogenous is strong. It implies that all taxation results in deadweight loss,[15] 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.

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:

$$F_W(w, e) = \Gamma(\varphi^{-1}(w, e), e). \tag{7}$$

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

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

[15] 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*).

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. Identification of the DD model requires both the imposition of parallel trends as well as variation in awareness of the tax to identify causal parameters. By contrast, the labor market model of Section 3 requires neither parallel trends nor 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 the additional variation that is available provides validating evidence.

Nevertheless, estimation of the model loosely follows the logic of the difference-in-differences approach by using the sample of women without children to estimate the bulk of the model's parameters.[16] 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 4.5 will examine untargeted moments from the estimation process.

[16] In the DD model, women without children identify the county type fixed effects.

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 the year 2005.

4.1 Identification

Appendix B provides a formal argument, under full awareness, that the structural primitives of the model are nonparametrically 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.

Informally, the identification argument works as follows. First, the distribution of accepted wages from job-to-job transitions within an hours class identifies the wage offer distribution up to the relative frequency of hours arrangements. Second, the distribution of part and full-time wages accepted out of unemployment identifies the distribution of reservation wages for each hours arrangement, and the relative frequency of hours arrangements accepted out of unemployment then identifies their relative frequency in the offer distribution. Observed rates of employment, job-to-job transitions, and employment to non-employment

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

transitions identify the rate parameters. Finally, ince there is a one-to-one mapping between work costs α and reservation wages, the distribution of the former is guaranteed by identification of the latter. This non-parametric identification argument also provides a rubric for estimation, which Section 4.3 will outline below.

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 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, which is identified in each county by the difference in the rate of employment by fertility status.

4.2 Comparing with the Difference-in-Differences Approach

In contrast, the difference-in-differences approach uses single women without children as a control group, imposing that differences between women with and without children aross counties are otherwise stable (parallel trends) to construct a counterfactual. The identification results that the previous section introduced assert that such assumptions are not necessary for the model. Despite this, the paper adopts an estimation approach that attempts to mimic the logic of the difference-in-differences strategy by imposing that contact rates and wage offer distributions are the same regardless of fertility status, and using women

[18] Although the wage offer distribution can be summarized parametrically, a distribution over firm types $\Gamma(p,e)$ can be inverted using equation (7) to rationalize the observed distribution. This is further discussed in subsection 4.4.

without children to pin down these primitives for each market type. A single parameter that shifts the location of the distribution of work costs (H) remains to explain differences in employment.

This approach warrants three further observations. First, although the estimation strategy attempts to mimic the difference-in-differences logic, it does not assume (nor does it imply) parallel trends in any outcome across county types. Thus, there is no guarantee that the model will arrive at the same inference regarding the impacts of the tax on employment and other outcomes. In this sense it should be viewed as an alternative set of assumptions for inferring the effect of the EITC and it will be useful to compare estimates under the two approaches. This is a statement about constructing counterfactuals. Both models could (and effectively do) exactly match observed outcomes for each county type and still disagree on their respective projections of the counterfactual.

Second, using single women without children to estimate the bulk of market primitives introduces a number of over-identifying restrictions: features of the data that the model need not necessarily match given that parameters are disciplined by other sources. A particularly important example is the EE rate for single mothers, which the estimation approach does not need to match in order to achieve identification. These untargeted moments are a useful source of validation for the estimated model.

Third, in order to coherently estimate the model, one must assume that the data represent a measurement of the economy in steady state. This would imply that the difference-in-difference approach is targeting (correctly or incorrectly, depending on the accuracy of parallel trends) the *long-run* impacts of the tax. It is important to note the potential difference between this practical approximation and reality: Chetty, Friedman and Saez (2013) document substantial growth and dispersion in bunching over time, consistent with gradual convergence toward full awareness. To the extent that the upcoming counterfactuals will issue a general caution about meaningful differences between short- and long-run impacts of the tax, this caution should be applied equally to the analysis and interpretation of results in Section 2, since awareness is likely growing during this period.

4.3 Estimation

This section outlines a simulated method of moments (SMM) procedure that selects moments based 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. 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.

4.4 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:

$$\hat{\varphi}(p, e) = \arg\max_{w} \hat{\Pi}(p, w, e) = \arg\max_{w} \left\{ (pe - w) \frac{\hat{g}_W(w, e)}{\hat{f}_W(w, e)} \right\}$$

where the symbol $\hat{\cdot}$ indicates that the model estimates are used in calculation. Following equation (7), Γ can be estimated non-parametrically as:

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

4.5 Model Estimates

Table 4 and Figure 2 provide a summary of the empirical moments that the SMM estimation procedure targets, along with the model's fit of these targeted moments. The model does a very good job in fitting the employment rates for both household types and the employment-to-employment transition rates women without children for all county types. Figure 2 suggests that 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]

As Section 4.1 noted, the model imposes a number of cross-equation restrictions that allow for identification without targeting all relevant moments. For example, the only difference between women with and without children in this model is a different location parameter μ_α which shifts the mean of the distribution of work costs (α). Thus, EE rates for women without children (which the estimation procedure targets) are sufficient to identify contact rates on the job for all workers. Can the model still replicate the EE rate for women with children across counties types? Table 5 shows that the model does largely matches those untargeted moments, and provides one source of validation for the model's mechanisms.

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

Table 4: SMM Procedure - Moments and Model Fit

	Data		Model
	Moment	SE of Moment	Moment
County Type 1			
Employment Rate - No Kids	0.7292	0.0092	0.7192
Employment Rate - Kids	0.7165	0.0104	0.7165
EE Rate - No Kids	0.0371	0.0020	0.0405
EU Rate - No Kids	0.0254	0.0008	0.0254
County Type 2			
Employment Rate - No Kids	0.7021	0.0053	0.6975
Employment Rate - Kids	0.7044	0.0067	0.7048
EE Rate - No Kids	0.0355	0.0011	0.0499
EU Rate - No Kids	0.0278	0.0008	0.0278
County Type 3			
Employment Rate - No Kids	0.6560	0.0083	0.6659
Employment Rate - Kids	0.6710	0.0124	0.6724
EE Rate - No Kids	0.0321	0.0016	0.0421
EU Rate - No Kids	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.

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 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.

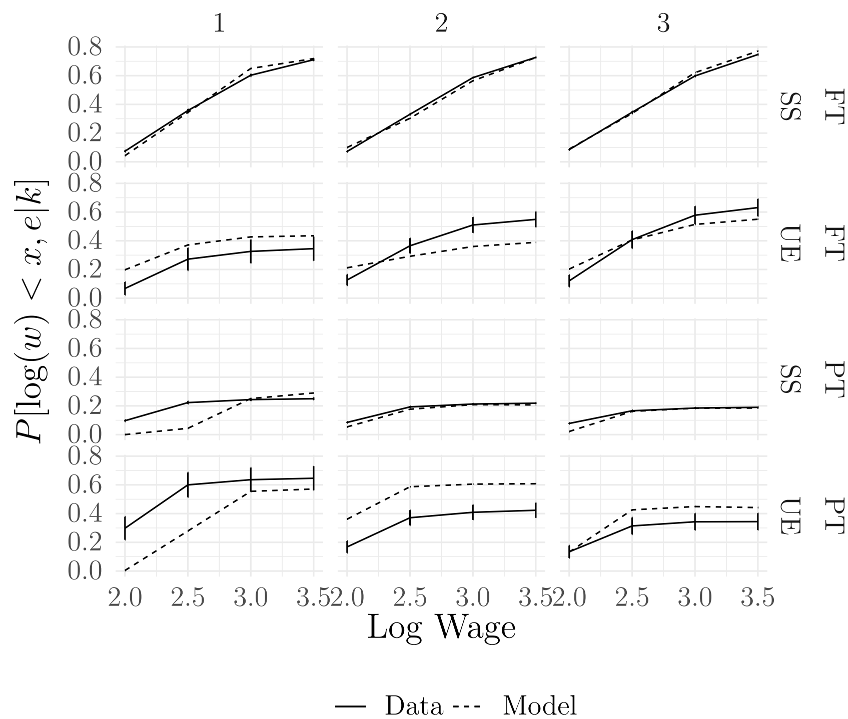
Table 5: Model Validation: EE Transition Rates for Women with Children

	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.

Figure 3 depicts the estimated distribution of firm productivities that rationalizes estimated wage offer distributions, as per Section 4.4. Both part-time and full-time distributions are highly right-skewed, although considerably lower for full-time firms.

Figure 2: SMM Procedure - Auxiliary Wage Moments



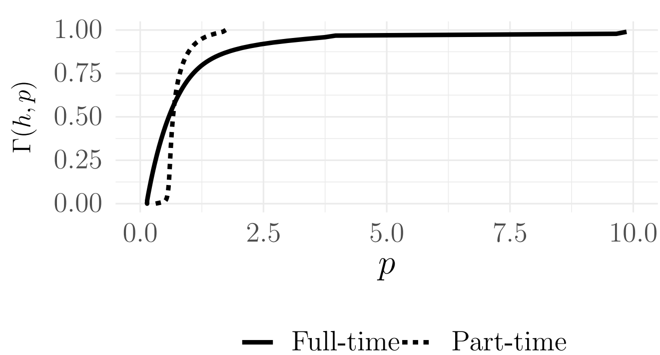
This figure shows the wage moments used in the SMM procedure together with the model's fit of these moments. Each data point shows the joint probability of an observed log wage less than or equal to $x \in \{2, 2.5, 3, 3.5\}$ with hours arrangement $e \in \{PT, FT\}$ in either the steady state (SS) or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

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 county-level replacement samples.

Figure 3: Productivity Distributions



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

5 Welfare and Sufficient Statistics

Prior studies of the EITC, and tax reforms in general, have emphasized a tight link between positive and normative impacts, showing that marginal changes in aggregate welfare typically depend on earnings elasticities and cross-sectional features of the earnings distribution (Feldstein, 1999; Eissa, Kleven and Kreiner, 2008*b*). The purpose of this section is to derive a welfare criterion and sufficient statistic for this model in order to maintain a connection and comparison with prior work. The key question is: how does (mis)measurement of the behavioral response to tax reforms translate to (mis)measurement of the welfare effects? This section presents two formulae that enable such a quantitative comparison using the estimated model. In order to avoid any confounding effects of partial awareness, the derivations below apply to the case where there is *full awareness* of the tax credit. Accordingly, the quantitative exercises in the next section will also be applied to an economy with full awareness.[20] The counterfactual exercises therefore ask: what are the long-run effects of the EITC once workers have learned about the program's incentives? This provides the most relevant benchmark for evaluating the program's steady-state impacts on labor market outcomes, especially when considering future marginal expansions, as in Section 6.2.

Define $x = (w, \alpha, e)$ as the vector summarizing an individual's dynamic decision problem, and define aggregate welfare as:

$$W = \mu \int e^{-rt}(wh - \alpha e - \tau(x))g_t(x)dxdt + \int e^{-rt}\tau(x)g_t(x)dxdt \tag{8}$$

where $\tau(x) = w - T(x)$ is the tax function (income net of transfers). This equation defines aggregate welfare as the aggregate discounted present value of utilities plus the discounted

[20] This assumption is motivated by the substantial temporal diffusion documented by Chetty, Friedman and Saez (2013). Sharp bunching rates increased nearly three-fold between 1996 and 2009, spreading geographically in patterns consistent with information diffusion through networks and the increased availability of tax preparation services. Given that more than 25 years have now elapsed since the major EITC expansion, and that Chetty, Friedman and Saez (2013) explicitly calculate policy impacts under the scenario where awareness reaches the levels observed in the highest-knowledge neighborhoods, it is reasonable to expect that most eligible individuals have by now learned about the program. Moreover, unlike the search frictions and hours constraints that are modeled as permanent features of the labor market, awareness is a transitional friction that can be eliminated through information diffusion and policy outreach.

present value of aggregate tax receipts. The parameter μ, by setting the planner's marginal valuation of individual consumption relative to the value of marginal public funds, indexes the planner's overall taste for redistribution to this group.

Now consider a marginal change in some parameter θ that defines the shape of the tax function τ. Appendix C shows that the marginal change in welfare can be written as:

$$\frac{dW}{d\theta} = \int e^{-rt} \left[\frac{d\tau(x)}{d\theta}(1-\mu) + \tau(x)\eta_t(x) \right] g_t(x) dx dt \tag{9}$$

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 marginal change. This is a sufficient statistic for the welfare impacts of the reform that depends on known objects (μ, τ, r) and potentially estimable features of the data (η_t, g_t).

The next section will employ two further simplifications to the welfare objective. First, a steady state assumption imposes that $g_t(x) = g(x)$ for all t. Second, setting $\mu = 1$ guarantees that welfare calculations will ignore redistributional concerns and quantify pure deadweight loss. This results in the pair of expressions:

$$rW = \int (w - \alpha e) g(x) dx \tag{10}$$

$$\frac{drW}{d\theta} = \int \tau(x)\eta(x) dx \tag{11}$$

Imagine now that a researcher has correctly derived this formula for marginal welfare effects, but has potentially mismeasured the behavioral elasticities η by using only short-run responses. Using the model to simulate dynamic adjustments to a marginal expansion, the next section uses these formulae to quantify the potential for this kind of mismeasurement of welfare effects.

6 Positive and Normative Effects of the EITC

This section conducts four exercises to gain insights into the welfare implications of the EITC. The first exercise calculates total employment and welfare effects of the EITC compared to a counterfactual without the tax credit. The second exercise calculates the welfare impact of a further marginal expansion of the tax credit. These first two exercises examine the potential for mismeasurement of employment and welfare effects (using equations (10) and (11)) by calculating differences between short and long-run responses.

Since search frictions in many models are consistent with firms having monopsony power (Manning, 2013, 2021), the third exercise 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.

The fourth and final exercise assesses the relative importance of hours constraints and search frictions for the overall pattern of results by manipulating the baseline model to remove each friction in isolation. In order to focus exclusively on the effect of the tax, each of the exercises below uses estimates from type 3 counties, where there is full awareness of the tax credit.

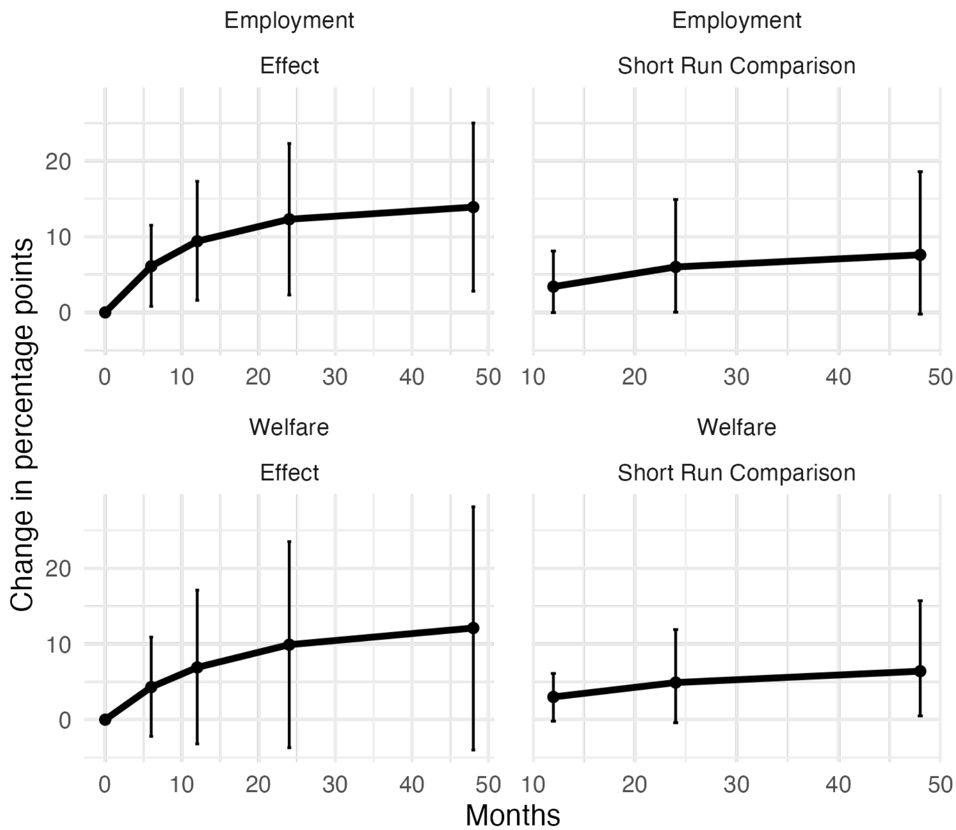
6.1 Short and Long-Run Effects of the EITC

In this section, we focus on evaluating tax changes for mothers under full awareness (i.e., county type 3).[21] Figure 4 compares an economy in steady state without the tax credit to an economy with the tax credit at different time horizons since its introduction. The top panel presents employment effects and the bottom panel presents welfare effects in percentage consumption equivalents relative to the baseline. The right column of Figure 4 recalculates the effects on employment and welfare relative to the 6 month horizon.

Reading from Figure 4, 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. As Section 4.2 explains, there is no reason to expect that these two models necessarily agree on employment effects, since the model does not assume and does not necessarily imply the parallel trends assumption used by the difference-in-differences approach to deduce impacts. However, it should be noted that the confidence intervals on this forecast are wide, suggesting

[21] 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.

that any discrepancy between the two estimates can be rationalized by sampling error.

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 Eissa, Kleven and Kreiner (2008*a*). Point estimates suggest that the EITC offsets other distortions and leads to welfare improvements of up to 12% of consumption in the long-run, but it should be noted that the confidence intervals contain zero at every horizon. 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.

6.2 Sufficient Statistics and Marginal Welfare Changes

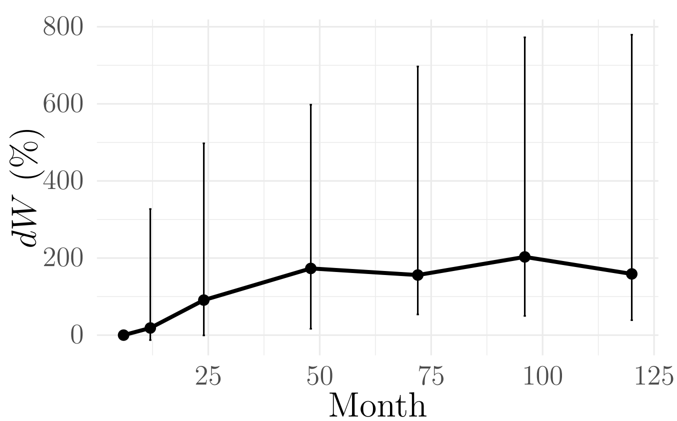
In order to connect these findings to a broader literature on normative tax policy analysis, this section uses equation (11)'s sufficient statistic to compare normative inference in the short versus the long-run. For ease of reference, this sufficient statistic is:

$$\frac{drW}{d\theta} = \int \tau(x)\eta(x)g(x)dx,\ \eta(x) = g(x)^{-1}\frac{dg(x)}{d\theta}.$$

The counterfactual in this section considers a "marginal" expansion of the EITC that increases the value of the credit by 10% at every earnings level. In practice, the marginal welfare change in the equation above corresponds simply to the change in total tax revenue that results from this expansion.

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 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.

This section concludes with an important clarification on interpretation of the paper's results for short versus long-run normative conclusions. Here, the short-run welfare effects represent *measured* effects on welfare using short-run responses, not the true effects of the policy on welfare in the short-run. With discount rates being close to zero, the effects of the tax on welfare in the short-run are quite well approximated by measurements in the long-run. Thus, one should not conclude that one can estimate welfare effects with short-run elasticities. Rather, the findings of this paper suggest that short-run estimates of elasticities may drastically underestimate the welfare effects of tax reforms.

6.3 Tax Effects with Endogenous Wages

The previous exercises take wages as exogenous when calculating outcomes and welfare. The welfare criterion in equation (10) 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 (10), 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 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).

6.4 Assessing the Role of Frictions

This section reconsiders the dynamic effects of the EITC on employment and EE transitions under two modifications to the baseline model. The first removes hours constraints by allowing workers to choose the hours arrangement that maximizes their utility. The second

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.

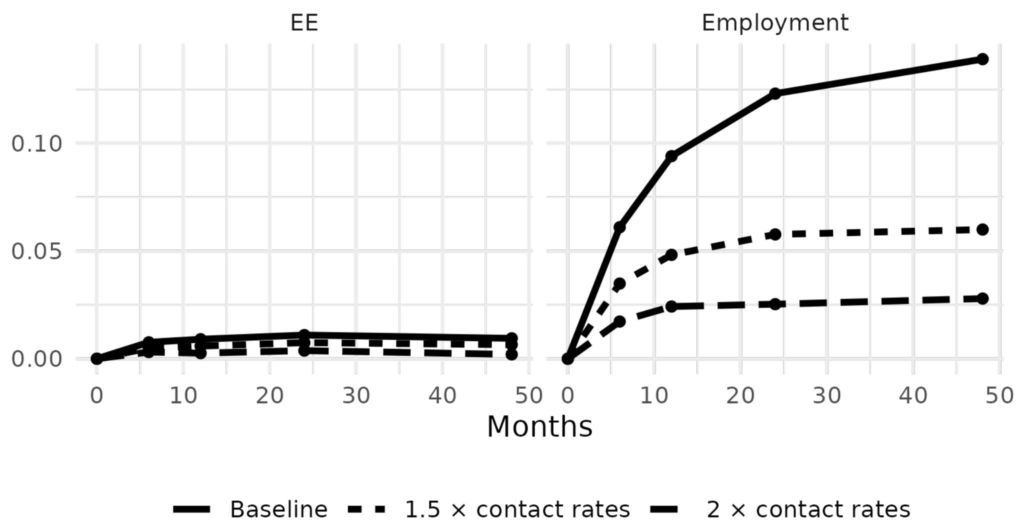
relaxes search frictions by uniformly scaling the magnitude of all contact rates. The exercise illuminates the respective influence of hours constraints and search frictions on the paper's core results, with two purposes in mind. On one hand, it tests the sensitivity of these results to the particular assumptions being made, and asks whether alternative specifications of the model can match the evidence equally well. On the other hand, they also demonstrate the respective role played by each friction in shaping the quantitative magnitudes of the model's predicted tax impacts.

The first alternative model allows all jobs to feature flexible hours so that, upon receiving an offer, individuals draw a wage and freely choose whether to work part-time or full-time. Figure 7 reports the effects of the EITC on employment and EE transitions at different horizons for single mothers for the baseline model and the model with flexible hours. The results demonstrate almost no effect on EE transitions, and an approximately 3 percentage point reduction in the employment response. These results are not surprising. As Section 3.3 explains, the increase in the EE rate in the model does not stem from workers suddenly wishing to work more but being unable to do so. Rather, it reflects a lowering of the first rung of the job ladder: unemployed workers accept lower-paying jobs that are subsequently easier to surpass with future offers.

Figure 7: Partial Equilibrium Effects of the EITC - Flexibility in Hours

These figures display the effects of the EITC on employment and job-to-job (EE) transitions for single mothers. The left (EE) and right (employment) panels report results over time for the baseline model and for the version with full hours flexibility.

Figure 8: Partial Equilibrium Effects of the EITC - The Role of Search Frictions



These figures display the effects of the EITC on employment and job-to-job (EE) transitions for single mothers. The left (EE) and right (employment) panels report results over time for the baseline model and for the versions with job arrival rates that are 50% and 100% larger.

In contrast to EE transitions, Figure 7 suggests that hours constraints do amplify the magnitude of employment responses. Much like EE rates, these effects also appear due to a reduction in workers' reservation wages, which causes workers to accept jobs that they would not accept in the absence of the tax. Estimates suggest that a substantial fraction of job offers are part-time, and part of the employment response here is due to an increased willingness to accept those jobs. Importantly, this is consistent with the evidence presented in Section 2, which suggested that workers do indeed respond to the tax by accepting more part-time work and more low wage jobs out of unemployment. Thus, the results here also highlight an important interaction between the two frictions.

Figure 8 compares the effects of the EITC on employment and EE transitions in the baseline to two counterfactuals where job arrival rates increase by 50%, and then 100%, respectively. As expected, when search frictions are relaxed, the gap between the long-term and short-term responses narrows relative to the baseline, with faster adjustment to the long-run steady state. Search frictions are also clearly important for matching the evidence on EE impacts: Figure 8 shows how the response in EE rates goes to zero as they dissipate. Again, this is not surprising: in the limit as search frictions dissipate, workers are already at the jobs they most prefer, leaving little scope for EE transitions to play a role. Fortunately, there is no need for the model's results to be robust to extreme parameterizations of search frictions, since observed transition rates essentially directly identify the correct values of these parameters within this class of models (see Section 4.1 for more details).

Taken together, the results here indicate that tax impacts are not overly sensitive to the specification of hours constraints. The counterfactuals also emphasise that search frictions play a crucial role in determining the model's ability to match and make sense of the empirical evidence.

7 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.

There are however some clear limitations to this paper's approach. First and foremost, the ultimate suggestions of the model's dynamic counterfactuals apply equally to the empirical results in Section 2 as they do to results more generally. Given the documented growth and diffusion of the sharp bunching measure, it is likely that the model – which makes a steady state assumption for tractability – has been estimated on data during a transitional period where awareness of the tax is growing. The data and moments used for the empirical and structural analysis would also, therefore, not embody the full effects of the tax. Although the structural approach may be slightly more immune to this issue, given that identification of the model's deep parameters depends jointly on transitional moments as well as cross-sectional ones, the potential for inconsistency is quite present. To this extent, a potential modeling extension that studies the EITC's effects in a non-stationary environment may be fruitful.

Second, our main focus is on single women. We feel that this is a particularly relevant group to study as the EITC is essentially targeted towards single-headed households with children. However, one implication is that we can only consider the results as they apply to the estimated population, since these do not necessarily generalize to the population at large. Third, while our model considers endogenous adjustments in wages, it does not consider endogenous search intensity, which creates an additional margin of adjustment that could affect both the speed of adjustment to changes in tax incentives, as well as the channels through which changes in marginal tax rates affect aggregate welfare, for example through the allocation of workers across jobs, as in Golosov, Maziero and Menzio (2013).

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A Additional Empirics

A.1 Subgroup Analysis and Robustness

Figure 9 presents estimates of $\hat{\gamma}$, derived from (6), for subgroups defined by education, sex, and marital status. Equation (4) expresses the causal parameter γ as the difference in differences between women with and without children and between the highest ($k = 3$) and lowest ($k = 1$) awareness county types. More generally, the model implies the moment conditions:

$$\mathbb{E}\left\{ (Y - \mu_k - \beta F - \gamma F \pi_k) \begin{bmatrix} 1 \\ F \\ F\pi_k \end{bmatrix} \Bigg| \; k \right\} = \mathbf{0} \tag{12}$$

for each county type. Analagously to the estimation of type-specific moments in (5), a posterior-weighted linear regression of each outcome Y on a type dummy, F, and awareness $\hat{\pi}_k$ targets these moment conditions to jointly identify (μ, β, γ). In practice, this results in sample moment conditions:

$$\sum_i q_{c(i)k}(Y_i - \mu_k - \beta F - \gamma F \hat{\pi}_k) = 0, \;\; k \in \{1, 2, 3\} \tag{13}$$

$$\sum_i \sum_k q_{c(i)k}(Y_i - \mu_k - \beta F - \gamma F \hat{\pi}_k) F = 0 \tag{14}$$

$$\sum_i \sum_k q_{c(i)k}(Y_i - \mu_k - \beta F - \gamma F \hat{\pi}_k) F \hat{\pi}_k = 0 \tag{15}$$

Figure 9 presents these estimates (labelled "regression") for comparison and verification that the simple estimator is robust to inclusion of additional identifying variation from county type (2).

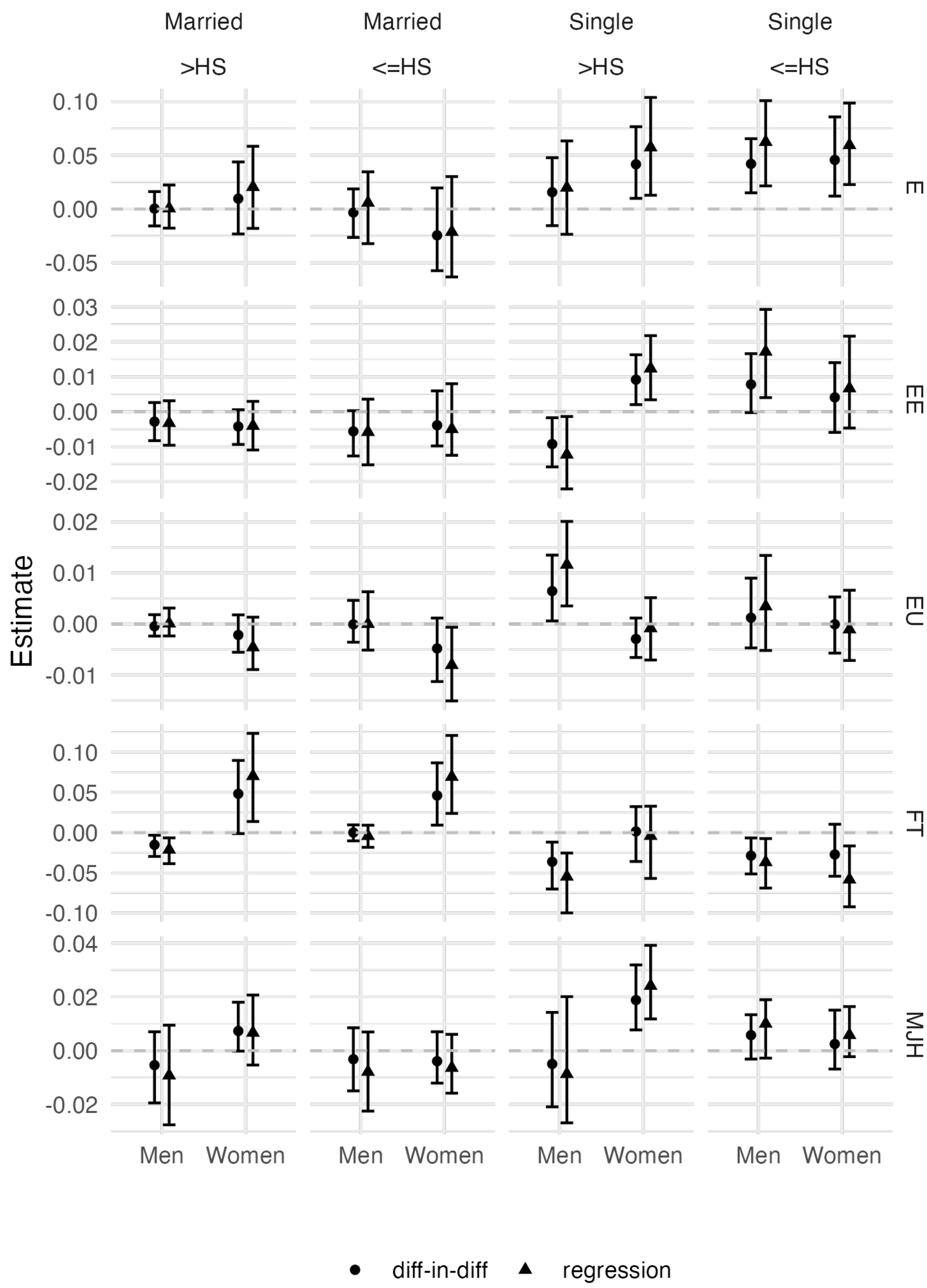
A.2 Regression-based Evidence

Table 7 presents regression estimates of the specification:

$$Y_i = \mu_{c(i)} + \eta_{t(i)} + \beta F_i + \tilde{\gamma} F_i B_{c(i)t(i)} + \zeta_i \tag{16}$$

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

Figure 9: Estimates of Tax Effects by Sub-group



This figure reports estimates from equations (6) (diff-in-diff) and (13)-(15) (regression), separately by education (at most a high school diploma versus some post-secondary education or more), sex, and marital status. Outcomes include employment (E), employer-to-employer transition rates (EE), employer-to-unemployment transition rates (EU), the share of employed individuals working full-time hours (FT), and the share holding multiple jobs (MJH). Confidence intervals are constructed using a county-level bootstrap with 200 replications.

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 ($\tilde{\gamma} = 0$). 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.

Table 7: Regression Evidence on the Effect of the EITC

	Emp	EE	MJH	FT
F	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)
$F \times B$	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 (16) 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 and are clustered at the county level.

Table 8 presents the results of a placebo test where women with 3 or more children act as a placebo treatment group relative to women with 1 or 2 children. The model is:

$$Y_i = \mu_{c(i)} + \eta_{t(i)} + \beta_1 F_i + \tilde{\gamma}_1 F_i B_{c(i)t(i)} + \beta_2 K_{3,i} + \tilde{\gamma}_2 K_{3,i} B_{c(i)t(i)} + \zeta_i \tag{17}$$

where $F_{3,i}$ 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.

Table 8: Robustness Test: Placebo Treatment

	Emp	EE	MJH	FT
F	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)
$F \times B$	0.281	0.050	0.076	-0.040
	(0.086)	(0.017)	(0.023)	(0.059)
F_3	-0.053	0.001	-0.010	-0.029
	(0.014)	(0.004)	(0.005)	(0.012)
$F_3 \times B$	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 (17) 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 and are clustered at the county level.

B Identification of the Model

This discussion supresses dependence of the parameters on fertility status or county type and applies (under full awareness) for any value of these variables. In what follows, recall that $u(\alpha)$ is the steady state fraction of workers of type α who are unemployed. Under full awareness, 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 $(G_W(\cdot,1), G_W(\cdot,2))$ 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:

$$f_W(w,1) = c f^*_W(w,1) \tag{18}$$

$$f_W(w,2) = (1-c) f^*_W(w,2) \tag{19}$$

$$\int f^*_W(w,e) dw = 1 \tag{20}$$

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. Aggregate welfare is:

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

Substituting in the definition of V, this objective is equivalently:

$$W = \mu \int e^{-rt} Z(x) \lambda_t(x|x_0) dx dt dG_0(x_0) + \int e^{-rt} \tau(x) dG_t(x) dt$$

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. As is standard, the effect of behavioral adjustments on welfare can be ignored due to the envelope theorem[22] giving the expression:

$$\frac{dW}{d\theta} = -\mu \int e^{-rt} \frac{d\tau(x_t)}{d\theta} \lambda_t(x|x_0) dx_t dt dG_0(x_0) + \int e^{-rt} \left(\frac{d\tau(x)}{d\theta} + \tau(x)\eta_t(x) \right) dG_t(x) dt$$

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:

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

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. Finally, imposing that the economy in steady

[22] More formally, let $\boldsymbol{r}$ be a function that summarizes all job acceptance decision rules. If $\boldsymbol{r}$ has been chosen to maximize $V(x_0) = \int e^{-rt} Z(x) \lambda_t(x|\boldsymbol{r}, x_0) dx dt$ then the equality $\int e^{-rt} Z(x) \partial\lambda_t[f](x|x_0) dt = 0$ must hold, where $\partial\lambda_t[f]$ is a functional derivative of λ_t with respect to the decision rule $\boldsymbol{r}$. In particular, this gives: $\int e^{-rt} Z(x) \partial\lambda_t[d\boldsymbol{r}/d\theta](x|x_0) dt = 0$, so the effect of behavioral adjustments on individual welfare can be ignored, as is standard.

state ($g_t = g$) and that $\mu = 1$ (which removes any inherent gains to redistribution toward this population) results in equations (10) and (11) in the main text.

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 10 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.

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

Figure 10: 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.

employment at a firm offering flow utility z. These values take the recursive representation:

$$(r+\zeta f)U_\alpha = T(0,a,f) + \lambda_0 \int \max\{0, V_\alpha(z) - U_\alpha\} dF_{Z|\alpha}(z) \tag{21}$$

$$(r+\zeta f)V_\alpha(z) = z + \lambda_1 \int \max\{0, V_\alpha(z') - V_\alpha(z)\} dF_{Z|\alpha}(z') + \delta(U_\alpha - V_\alpha(z)). \tag{22}$$

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

$$V'_\alpha(z) = \frac{1}{r+\zeta f+\delta+\lambda_1 \tilde{F}_{Z|\alpha}(z)} \tag{23}$$

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 (23) 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:

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

F Discussion of the Awareness Measure

The difference-in-differences evidence in this paper relies on geographic variation in awareness of the EITC. This approach is adopted directly from Chetty, Friedman and Saez (2013), who compose a proxy of awareness using sharp bunching in self-employment earnings.

Sharp bunching is defined as the percentage of EITC claimants with children who report total earnings within \$500 of the first kink of the EITC schedule (the refund-maximizing income level) and have non-zero self-employment income. Unlike wage earnings, which are third-party reported to the IRS on W-2 forms, self-employment income has minimal reporting requirements and can be easily manipulated. Chetty, Friedman and Saez (2013) document that self-employed tax filers exhibit sharp bunching at the first kink of the EITC schedule, with the degree of bunching varying substantially across geographic areas. For example, 6.5 percent of EITC claimants in Chicago reported self-employment earnings exactly at the refund-maximizing level in 2008, compared with only 0.6 percent in Rapid City, SD. Critically, this measure also exhibits temporal diffusion consistent with information spreading through networks: the degree of sharp bunching was nearly three times larger in 2009 than in 1996, shortly after the EITC was expanded to its current form.

Chetty, Friedman and Saez (2013) provide extensive validation that spatial variation in sharp bunching reflects differences in knowledge about the EITC schedule rather than other factors such as local tax compliance rates or preferences. First, they show that individuals who move from low-bunching to high-bunching neighborhoods increase their EITC refunds after the move, while those who move in the opposite direction experience no change in refunds—a pattern consistent with learning but not forgetting. Second, sharp bunching is highly correlated with predictors of information diffusion, such as the local density of EITC recipients and the availability of professional tax preparers, but is uncorrelated with state-level measures of tax non-compliance among non-EITC recipients. Third, and most importantly for establishing that the measure captures knowledge about the entire EITC schedule rather than just the kink point, Chetty, Friedman and Saez (2013) demonstrate that individuals in low-bunching areas exhibit virtually no change in the distribution of reported self-employment income when they become eligible for a substantially larger EITC refund after having their first child. In contrast, the distribution of self-employment income in high-bunching areas concentrates sharply around the refund-maximizing kink following child birth. This evidence indicates that individuals in low-bunching areas are unaware of marginal incentives throughout the EITC schedule and can therefore serve as a valid counterfactual for behavior in the absence of the EITC.

The use of sharp bunching as a proxy for awareness is particularly well-suited for studying single mothers, the primary focus of this paper. Single mothers comprise the vast majority of EITC-eligible households with children: in the cross-sectional analysis sample used by Chetty, Friedman and Saez (2013), 70 percent of single filers are female and only 30 percent of filers are married. Moreover, the program's structure—with eligibility and benefit levels determined by the presence of qualifying children and income thresholds that correspond to typical earnings of single parents—implicitly targets this demographic. The fact that Chetty, Friedman and Saez (2013) document substantial intensive-margin earnings responses among wage earners in high-bunching areas, with approximately 75 percent of the increase in EITC refunds coming from individuals who change the amount they earn rather than whether they work, suggests that the awareness measure captures variation in knowledge that is directly relevant for understanding labor supply responses along multiple margins.