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

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Abstract

In this paper we consider the behavioral response of workers to changes in tax incentives when faced with hours constraints and search frictions. In this setting, workers can respond by transitioning into employment, transitioning to new jobs, or accepting second jobs. We provide empirical evidence that all three adjustments are positive and significant in the response of single mothers to the Earned Income Tax Credit. We then estimate a frictional search model with hours constraints and multiple job holding that fits our empirical evidence, and use the model to explore the positive and normative implications of these frictions for tax policy analysis. We find that long-run employment elasticities are up to 73% larger than the short-run elasticity, which has direct implications for welfare analysis using deadweight loss tax formulae. We use the model to demonstrate that the degree of search frictions in a labor market, as measured by contact rates and job destruction rates, directly affects the welfare gains from the introduction of the EITC in addition to other counterfactual tax credit schedules.

1 Introduction

The neoclassical model of labor supply is a workhorse tool for tax policy analysis. Supposing that workers can freely adjust their hours of work, given a particular wage, the model offers compensated and uncompensated structural elasticities that prove to be crucial in deciding the optimality of tax schedules (Mirrlees, 1971; Diamond, 1998; Saez, 2001), and measuring the dead weight loss from income taxes (Harberger, 1964; Feldstein, 1999).

In this paper we consider the implications of two important departures from the neoclassical model. First, jobs may be accompanied by constraints on hours worked. When this friction prevails, employed workers must respond to changes in tax incentives by either switching to new jobs, or taking second jobs. Second, these adjustments

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are constrained by the stochastical arrival of new job opportunities in a labor market characterized by search frictions. The contribution of this paper is to document novel evidence of these frictions, and to derive positive and normative implications by matching the evidence to a dynamic model of on-the-job search with hours constraints and multiple job holding.

To provide evidence, we examine the response of single mothers in the United States to the Earned Income Tax Credit (EITC)[1], looking at responses in employment, multiple job holding (MJH), and employer-employer (EE) transitions. Our empirical strategy exploits within-county variation over time in the "sharp bunching" measure of Chetty, Friedman and Saez (2013), the excess mass of earnings reported by self-employed workers at the refund-maximizing kink in the EITC schedule. Chetty, Friedman and Saez (2013) comprehensively validate this measure as a proxy for local awareness of the EITC. For each outcome of interest, we examine how differences between eligible and ineligible individuals evolve in response to within-county variation in the awareness proxy. The key identifying assumption here is that, while the bunching measure may indirectly proxy for economic primitives that are also associated with the outcome, there is no difference in how this selection by eligibility evolves over time.

We use the design to estimate responses to the EITC in employment, multiple job holding, and job-to-job transitions, finding that all three measures respond positively to awareness of the EITC. In the case of the latter two margins of response, we draw two conclusions. First, while neither is predicted by the neoclassical model, both are consistent with a model in which employed workers can only adjust to the change in incentives by taking second jobs, or transitioning to new jobs. Second, while intensive marginal responses in the form of hours do not appear to be significant, using this design or any other (Meyer and Rosenbaum, 2001; Eissa and Hoynes, 2006), these results uncover a margin of response for employed workers that is significant. When combined with the work of Blundell, Brewer and Francesconi (2008), who show that hours responses to a tax reform in the United Kingdom are due largely to workers taking new jobs, the evidence points to frictions of this style as a useful framework for tax policy analysis. In theory, only hours constraints are required to rationalize the empirical evidence that we contribute, however this insight is enhanced, and the data more readily interpreted, when embedded in a labor market with search frictions.

In the second stage of our analysis, we explore the positive and normative implications of these frictions using a dynamic search model with hours constraints, on-the-job search, and multiple job holding.[2] While this structural analysis poses a typical problem, where full specification of the model requires high level assumptions about the data generating process that are hard to test directly, we attempt to maximize the credibility of the exercise by imposing that the model replicates our empirical analysis in the first stage,

[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.

[2] When we describe the model, we highlight which features are shared by other work, but notable examples are Guler, Guvenen and Violante (2012), Flabbi and Mabli (2018), Bloemen (2008), Paxson and Sicherman (1996), Gørgens (2002), and Lalé (2019).

in addition to important cross-sectional and panel features of the data. Thus, our choice of parameters that determine worker preferences over the extensive and intensive margin inherit the credibility of the first stage design. We use the estimated model to perform three main exercises. In the first exercise, we compare contemporaneous responses to the tax to those found in the long-run, when adequate time is provided to adjust to the new policy. In the second, we calculate a consumption equivalent measure of the welfare gain from the tax, and explore the importance of the search environment for this finding. In the third, as an illustrative policy exercise, we compare the EITC to a revenue-equivalent Negative Income Tax.

In our first quantitative exercise, we consider the measurement issues introduced by labor market frictions. Of particular interest is the dynamic pattern of worker responses to changes in incentives, which are harder to measure than corresponding short-run adjustments. A key distinction between the neoclassical model and labor market models with search frictions is that the distribution of workers over jobs is a *stock* variable rather than a choice, and should therefore be analyzed by characterizing corresponding *flows*. This is the approach we take here, disciplining our parameters by matching evidence on worker flows and using this to forecast long-run steady state counterfactuals.

While contemporaneous responses to changes in tax policy are well-studied, our analysis suggests that these could understate the true impact of the reform, for the simple reason that costly or frictional adjustments take time. For unemployed workers, adjustment is constrained by the arrival rate of job offers. For employed workers, responding to the policy requires them to take second jobs, or to find new jobs that better accommodate their preferences over the intensive margin. Both adjustments are also constrained by the rate at which job offers arrive while working. In our main counterfactual exercise, we find that in the short-run, the EITC leads to a 5.7 percentage point increase in monthly employment, a 0.09 percentage point increase in the monthly rate of MJH, and a 0.42 percentage point increase in the monthly rate of EE transitions. By contrast, the long-run (steady state) impact on employment is 9.9 percentage points, on MJH is 1.86 percentage points, and on EE transitions is 0.64 percentage points.

Turning to the normative implications of our exercise, we first note that these frictional dynamics have direct implications for deadweight loss calculations in the spirit of Feldstein (1999) and Eissa, Kleven and Kreiner (2008), that rely in their empirical implementation on contemporaneous participation and hours elasticities, and assume away the frictions that we show here to be relevant.

Next, we use the estimated model to calculate the welfare effects from the introduction of the EITC, finding long-run gains equivalent to a 4.16% lifetime increase in consumption. The dynamics of the model are crucial for this calculation, as job destruction and contact rates shape income risk, and consequently the dynamic incidence of the tax for individuals. When combined with preference estimates, disciplined here by estimated behavioral responses, these dynamics also determine the demand for insurance in the cross-section, which is an important component of the welfare gain from the tax. In order to better understand the relevant contribution of these two channels to welfare, we derive a formula for the response of welfare in this model to marginal tax reforms. This formula allows a decomposition of the welfare gains from marginal expansions in the EITC into an *incidence* effect and *insurance* effect. We find that both channels are quantitatively relevant, with incidence effects an order of magnitude larger than insurance effects for the EITC.

Finally, we can use the estimated model to compare the EITC with other policies, such as a Negative Income Tax (NIT). We find that, when chosen to maximize average willingness to pay for the program, the optimal NIT is valued, on average, as equivalent to a permanent 2.07% increase in consumption. As such, the optimal NIT is not valued by any of the agents in our model as highly as the EITC. The same mechanism as in Saez (2002) is present here: extensive margin adjustments are significant, while responses in terms of job acceptance decisions have a minor effect on tax collections. This finding contributes to an ongoing policy discussion that compares these two means of redistribution (Rothstein, 2010; Saez, 2002), with the key distinction being our departure from the neoclassical framework for welfare analysis. In this respect, we contribute to a small literature on optimal tax policy in frictional labor markets. In models of search, tax schedules have efficiency consequences through wage-setting and job creation (Hungerbühler et al., 2006), through the directed search effort of workers (Golosov, Maziero and Menzio, 2013), and through job-to-job mobility (Bagger et al., 2018). Of these, our paper is closest in spirit to Bagger et al. (2018), who also examine taxable income elasticities through the lens of job-to-job mobility, using an equilibrium job-ladder model with complete markets.

The insight that frictions will complicate interpretation of estimated behavioral responses is far from novel. Dickens and Lundberg (1993), for example, estimate a model of labor supply in which finitely many hours choices are drawn from a distribution, and use the empirical framework to warn researchers of the potential for bias in estimated elasticities. Even so, a cautious consensus has emerged that while extensive (i.e. participation) marginal elasticities are of significant quantitative magnitude, intensive marginal elasticities are less relevant. The EITC has been an influential proving ground for this notion. While much prior work argues that the EITC encourages employment (Eissa and Liebman, 1996; Meyer and Rosenbaum, 2001; Grogger, 2003; Hotz and Scholz, 2006)[3], there is a paucity of evidence for adjustments in hours worked (Eissa and Hoynes, 2006; Meyer and Rosenbaum, 2001; Rothstein, 2010). However Chetty (2012), in revisiting conclusions from these and similar tax reforms, shows that when a partially specified friction of adjustment is added to the neoclassical model, even small frictions can obviate the estimation of compensated elasticities from price changes, with bounds that comfortably encompass the range of elasticities found in the literature.

While the work of Chetty (2012) provides an elegant and quite general analysis of the frictions necessary to reconcile available empirical evidence, it has, by design, little to say about the nature of the market imperfections at play. Nor does it, strictly speaking, nest

[3]In a recent paper, Kleven (2020) has questioned the robustness of these findings to specifications that adequately control for contemporaneous events. Since we do not follow the same event study design, the findings of this paper, along with the original findings of Chetty, Friedman and Saez (2013), can be viewed as a contribution to this debate.

the class of models from which we develop our analysis, where the pertinent frictions must be described in a fundamentally dynamic setting. By adopting a model in which frictions to adjustment are fully articulated, we also take a stand on the features of the data generating process that are policy-invariant, identify economic primitives that permit *ex-ante* policy evaluation (Heckman and Vytlacil, 2005), and provide a specific theoretical link between transitional and steady-state policy elasticities. In this spirit, we see a connection between our approach and lessons from the literature on pricing frictions, in which subtle differences in specification of menu cost models lead to quite different predictions for monetary policy (Caplin and Spulber, 1987; Golosov and Lucas Jr., 2007; Midrigan, 2011). The only solution to that problem, as is also the case here, is to pay attention to which models are most readily brought to bear on empirical evidence (Nakamura and Steinsson, 2008).

It is tempting to argue that regardless of whether the source of statistically negligible elasticities is preferences or constraints, only the reduced-form elasticity is required for policy analysis. This is true, for example, in calculations of deadweight loss, where the overall behavioral response is a sufficient statistic (Chetty, 2009). Eissa, Kleven and Kreiner (2008) derive such a formula for the EITC, finding that welfare gains (as measured by reductions in deadweight loss) from the tax change are driven almost entirely by responses at the extensive margin, a direct implication of the consensus that hours responses don't appear to be a relevant margin of adjustment. Our analysis in this paper recasts this finding as one driven by contemporaneous responses, and attempts to complement it with an exploration of the nature, timing, and implications of frictions in the long-run. A fully-specified dynamic model is our preferred tool for this analysis, and is, given the large number of reduced form elasticites that would otherwise be required for this analysis, potentially crucial, as argued by Kleven (2018).

The rest of the paper is structured as follows. In Section 2, we document our empirical evidence on the response of employment, multiple job holding, and employer-employer transitions to the EITC. In Section 3, we describe and briefly analyze the model we use to interpret these findings, in addition to describing our estimation procedure. In Section 4, we perform our positive and normative analysis of the tax using counterfactuals from the estimated model. Section 5 offers concluding thoughts.

2 Frictional Response to the EITC: Some Empirical Evidence

2.1 Empirical Strategy

We examine the response of single monthers in the United States to the EITC. Details of the EITC structure are provided in Appendix B. To study the response of workers to the credit, we adopt the empirical strategy of Chetty, Friedman and Saez (2013) who, in tax return data, use the excess bunching of self-reported incomes at the refund-maximizing kink in the schedule as a proxy for neighborhood-level awareness of the tax credit. To describe this design, it is useful to first outline the classic difference-in-differences estimator used, for example, in Meyer and Rosenbaum (2001). Let Y_{ict} be the outcome of interest for person i in county c at time t, let K_{it} indicate the presence of dependent children in the household, and let T_t be an indicator for whether the tax has been introduced in this time period. The regression:

$$Y_{ict} = \mu_t + X_{ict}\beta + \gamma_0 K_{it} + \gamma_1 K_{it} T_t + \epsilon_{ict} \tag{1}$$

is designed to uncover the effect, γ_1, of the tax reform T_t on eligible individuals ($K_{it} = 1$) using untreated individuals ($K_{it} = 0$) as the effective control group. The design is valid under the assumption that the difference between eligible and ineligible individuals, γ_0, is stable over time such that, μ_t, the time-specific fixed effect, is a sufficient control for trends[4]. The control variables here, X_{ict}, are chosen to allow for other potential changes that occur contemporaneously with the introduction of the reform, and ideally increase the robustness of the identification assumption[5].

Suppose now that instead of using variation in the timing of the tax, T_t, we leverage variation in whether individuals are *aware* of the tax, assuming that lack of awareness is behaviorally equivalent to no tax. Letting D_{it} indicate awareness, we can write a linear model of outcomes:

$$\mathbb{E}[Y_{ict}|X_{ict}, K_{it}, D_{it}] = \mu_t + X_{ict}\beta + \gamma_0 K_{it} + \gamma_1 K_{it} D_{it} \tag{2}$$

This equation cannot be used because D_{it} is not observed. The innovation of Chetty, Friedman and Saez (2013) is to use the excess bunching in the reported earnings of self-employed workers at the refund-maximizing kink. We refer to that paper for comprehensive validation of this variable as a proxy for awareness. Letting this variable in county c at time t be denoted by B_{ct}, we augment the model in (2) with this relationship:

$$\mathbb{E}[Y_{ict}|X_{ict}, K_{it}, B_{ct}] = \mu_t + X_{ict}\beta + \gamma_0 K_{ict} + \gamma_1 K_{ict}\mathbb{E}[D_{it}|B_{ct}] \tag{3}$$

$$\mathbb{E}[D_{ict}|B_{ct}] = \mu_c + \gamma_B B_{ct} \tag{4}$$

Writing the model in this way requires an identification assumption that the bunching measure does not provide any additional information on the differences between eligible and ineligible individuals, beyond it's relationship with treatment. We spell out the nature of this assumption in more detail below. Taking this model as given, our chosen specification for empirical analysis is:

$$Y_{ict} = \mu_t + \omega_c + X_{it}\beta + \gamma_0 K_{ict} + \tilde{\gamma}_1 K_{ict} B_{ct} + \epsilon_{ict} \tag{5}$$

where we have explicitly added county fixed effects (ω_c), and X_{ict} contains dummies for age, education, and race, as well as the bunching variable, B_{ct}. We finally clarify two aspects of this design.

[4] This is the parallel trends assumption

[5] A recent paper by Kleven (2020) questions the adequacy of these controls in studies that use this design, and that contemporaneous changes in state welfare policies might confound popular estimates of the effect of the EITC.

First, the coefficient $\tilde{\gamma}_1$ is equal to $\gamma_1 \times \gamma_B$, which can be interpreted as the effect of the tax (γ_1), scaled by the association between bunching and awareness, γ_B. Thus, if B_{ct} is an appropriate proxy for the probability of individual awareness within a county-time pair, $\tilde{\gamma}_1$ identifies the sign but not the magnitude of γ_1. When taking these regressions to the model we will make an additional scale normalization in the measurement relationship between bunching and awareness in order to identify these two effects separately.

Second, the key identifying assumption using this specification is that within a county, temporal variation in the bunching measure is not correlated with temporal variation in the difference between eligible and ineligible individuals. Relating this specification back to the classic design outlined in (1), within-county variation in bunching can be interpreted as an exogenous source of variation in the *intensity of treatment* at the county level.

2.2 Data Sources and Construction

Our data on outcomes and demographics are taken from the IPUMS monthly CPS file extracts (Flood et al., 2018), using all months in the years 2000 to 2009. In our main sample, we keep non-military individuals between the ages of 18 and 55 (inclusive), restricting our attention to unmarried women. In later robustness tests, we will examine results for a pooled sample (both married and unmarried women), as well as younger (aged 18 to 40) married women, and a pooled sample of young (18 to 40) married and unmarried women. Descriptive statistics for each sample can be found in Table 1. The average levels of our outcome variables are in line with other studies (Lalé, 2015; Fujita, Moscarini and Postel-Vinay, 2019), although slight discrepancies are expected given our chosen sample.

Our three binary outcome variables of interest are (1) employment, which is equal to one only for those who report currently being at work last week; (2) multiple job holding (MJH), which we define as equal to one if an individual reports working in more than one job in the previous week; and (3) job-to-job transitions (EE). This last variable is defined only for a subsample of individuals: those who appear in consecutive months of the sample, and are employed in both months. This variable is coded to 0 if an employed individual reports that they are still working for the same employer as the previous month, and 1 if they report otherwise.

One issue worthy of further discussion is our method of inferring a job-to-job transition, using linked monthly files. Fujita, Moscarini and Postel-Vinay (2019) document that, due to a 2007 change in the CPS survey methodology, this method may understate the overall rate of EE transitions in the economy. While we are wary of this measurement issue, it is not clear how this would affect measurement of the responsiveness of transitions to tax changes, and whether any method of imputation (which necessarily injects noise into the outcome variable) would help or exacerbate this problem. We do not offer a solution to this potential measurement issue in this paper, but do note it for the sake of transparency.

The monthly files also provide information on the race, education, age, and marital status of individuals, as well as the number of children that currently reside in the

Table 1: Descriptive Statistics

	Main Sample	Pooled	Young	Young Pooled
Employed (%)	69.27	67.21	67.95	65.13
MJH (%)	4.74	4.04	4.51	3.86
EE (%)	3.10	2.58	3.56	3.01
Frac. White (%)	70.30	76.12	70.48	75.12
Frac. Black (%)	20.53	13.92	19.63	14.36
Child in Home (%)	33.94	54.05	29.63	50.96
Mean Number of Children	0.60	1.04	0.54	1.02
Less than High School (%)	13.25	11.67	13.59	12.72
High School (%)	27.59	27.41	26.72	26.16
Bachelor's or Higher (%)	24.77	30.22	23.47	29.05
N. Obs	832,234	1,796,952	569,199	1,052,735

This table presents descriptive statistics for each of the four samples of CPS monthly files (2000-2009) used in our regression analysis. Our main sample is unmarried women aged 18 to 55. The Pooled sample includes married women as well as unmarried women, aged 18 to 55. The Young sample is unmarried women aged 18 to 40, while the Young Pooled sample comprises all women aged 18 to 40.

household, of any age. We use this latter variable to distinguish between eligible and ineligible individuals (those with no children in the household). Our view is that this variable will accurately define eligibility in the large majority of cases, although there is some chance that older individuals may have offspring with them in the household who are now adults, rendering them ineligible for the EITC. While the focus of our results is on unmarried women, aged between 18 and 55, to explore the sensitivity of our analysis to this potential measurement issue, we will also examine results for a pooled sample of married and unmarried women, as well as for a sample restricted to women between the ages of 18 and 40.

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, we create a county-level bunching measure using the 2010 Census Zip Code Tabulation Area (ZCTA) to County relationship file.[6] Using population counts from this file, we compute the fraction of the population in county c that resides within the 3-digit zip code z, w_{czt}. Our 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

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

Table 2: EITC Sharp Bunching Regression - Single Women, 18-55

	Emp	MJH	J2J
	(1)	(2)	(3)
K	-0.012*	-0.009***	-0.005**
	(0.005)	(0.002)	(0.002)
B	-0.901***	-0.233**	-0.217**
	(0.226)	(0.089)	(0.078)
$K \times B$	0.517***	0.225***	0.096*
	(0.151)	(0.063)	(0.038)
county	Yes	Yes	Yes
date	Yes	Yes	Yes
age	Yes	Yes	Yes
educ	Yes	Yes	Yes
race	Yes	Yes	Yes
Estimator	OLS	OLS	OLS
N	799,920	786,131	360,050
R^2	0.095	0.019	0.007

Columns show results for (1) Employment; (2) Multiple Job Holding; (3) Job-to-Job transitions. Standard errors clustered at the state level. *** stands for p-value<0.01, ** stands for p-value<0.05, * stands for p-value<0.1.

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, we expect our constructed proxy to adequately serve the same purpose.

2.3 Results

We run specification (5) on each of the three outcome variables: employment, multiple job holding, and job-to-job transitions. Since unmarried mothers are the key population of interest in studies of the EITC, our major focus will be on these individuals. However, we also run the specification on all women (married and unmarried). All standard errors reported below are calculated allowing for arbitrary covariance structure at the state level.

Table 2 holds our coefficient estimates for the three outcome variables of interest when using the sample of single (i.e. unmarried) women between the ages of 18 and 55. We will sometimes refer to this as the main sample. The third row reports coefficient estimates for $\tilde{\gamma}_1$, on the interaction between having dependent children, K_{ict}, and county-level bunching at time t, B_{ct}. We find positive employment effects.[7] The magnitude of our estimate for single mothers is comparable with the employment effects estimated in Chetty, Friedman and Saez (2013), which we take as some validation of our identification strategy. As we discussed previously, the scale of the true employment effect is not identified here without further restriction, however the reader can interpret the estimate as follows (making the necessary assumptions for a causal interpretation): a 1% point increase in the EITC awareness proxy, within a county, leads to a 0.52% point increase in the employment of eligible women in that county.

Turning to multiple job holding, we find a significant positive effect of EITC awareness, with a magnitude of just under half of the employment effect. Throughout this paper, we have advanced a specific interpretation of this result: that some women respond to changes in the incentives provided by the tax credit by taking second jobs.[8] If these results are to be believed, they reveal a theorized (Shishko and Rostker, 1976) but heretofore unobserved role for MJH in the labor market, as a means for adjustment of hours at the intensive margin. If the introduction of the EITC increases the returns to work for single mothers, yet their current job provides no opportunity to increase hours, taking a second job is one way to increase hours of work in the face of these frictions.[9] In recent work, Tazhitdinova (2017) estimates the responsiveness of multiple job holding to changes in tax incentives in Germany, finding sizeable participation elasticities. Taken together, these results offer compelling evidence that the satisfaction of preferences over the intensive margin is a key driver of MJH behavior.

An additional implication of hours constraints is that workers may search for and accept new jobs in response to changes in tax incentives. This observation is useful, not just because it offers an opportunity to learn about the relevance of hours constraints and search frictions in the labor market, but also because it offers an index of adjustment that responds unambiguously to changes in incentives. While the effect of the EITC on hours is ambiguous (depending on whether the individual is situated on the phase-in, plateau, or phase-out region of the credit schedule), its effect on these transitions is unambiguous, in that both downward and upward adjustments may require a transition to a new employer.

Accordingly, we next examine whether the probability of job-to-job transitions is responsive to EITC awareness. The third column of Table 2 asserts that for single mothers, the answer to this is affirmative. A 1% point increase in the county awareness proxy leads to a 0.096% point increase in the rate of EE transitions. This finding is consistent with our initial hypothesis that workers facing hours constraints can also take

[7]We also find positive employment effects for single and married fathers. These results are available upon request.

[8]It is worth noting that, depending on where an individual currently resides on the credit schedule, awareness of the EITC may cause individuals to quit their second jobs, through an income effect. This is ultimately an empirical question.

[9]While Chetty, Friedman and Saez (2013) do not observe MJH per se, they do find a significant impact of EITC awareness on the number of jobs held within a year, and provide a similar interpretation of this finding. We interpret their result as the combination of the two effects we find here: individuals both taking second jobs and switching to new jobs. When aggregated to the annual level with tax data, it is impossible to distinguish between these effects.

new jobs (as well as second jobs) that better suit their preferences over the intensive margin, in response to tax changes. It is also consistent with work by Bagger et al. (2018), who provide evidence that reductions in marginal tax rates in Denmark lead to an increase in job-to-job transitions. We view this result as quite significant for the two reasons we introduced above. First, it validates a view of the labor market in which hours constraints and search frictions interact with each other. Second, it confirms that adjustments to work arrangements beyond the employment participation margin do indeed occur, but may happen across (rather than within) jobs.

2.3.1 Different Samples

As mentioned previously, there is some concern about how noisy our measure of eligibility, the number of own children in the household, truly is. There is some chance that older individuals may have offspring with them in the household who are now adults, rendering them ineligible for the EITC. To address this concern, we run our preferred specification on both married and unmarried women (Table 9), on unmarried women between 18 and 40 (Table 10), and on both married and unmarried women between 18 and 40 (Table 11). We will respectively refer to these samples as the pooled sample, the young sample, and the young pooled sample. The tables (which can be found in Appendix A) replicate, with modest changes in magnitudes, the results from our regressions on the main sample of interest. Given that the effect of the EITC is likely to be moderated both by age and marital status, some change in effect sizes is expected, though we are encouraged by the consistency of the pattern of results across the different samples.

2.3.2 Effect on Total Hours

Since the design we adopt here is somewhat different to traditional difference-in-difference analyses, and the awareness proxy brings potentially richer variation than that which is used in other studies, it is worth examining whether this new specification can detect any effect on total hours worked. In Table 12, we run our model on total hours worked for the four subsamples (main sample, pooled sample, the young sample, and the young pooled sample). We find no significant effects for any of these groups, consistent with the prior literature. Theoretically, since the EITC can both encourage and discourage work, depending on where an individual is located on the credit schedule, there is no reason to expect an unambiguous effect on hours. In contrast, our chosen outcomes of interest: multiple job holding and job-to-job transitions, are more easily detectable margins of adjustment.

2.3.3 Placebo Tests

A key concern is that the bunching measure, B_{ct}, which is related to self employment, is correlated with local economic conditions or trends that affect individuals of different sized households differently. This would clearly violate our identifying assumption and yield spurious estimates. To examine this possibility, we run three placebo tests on each of the three outcome variables, where we compare individuals with two or fewer children in the household to those with three or more. Since all such individuals are eligible for the EITC, we should not see different impacts of awareness (as proxied by bunching), unless the aforementioned latent associations are driving results. We run placebo regressions on the main sample of single women (Table 13) and the pooled sample of married and unmarried women (Table 14). The results show that the model passes this placebo test in each case: there is no significant difference in the behavioral response for women with three or more children in the household, for any sample or outcome variable.

To further examine the validity of our identifying assumption, we use outcome variables that should be, in general, exogenous with respect to tax policy. In this case, significant estimates using our research design might indicate a violation of their identifying assumptions. Our chosen outcomes of interest are race (a binary variable indicating if the individual is nonwhite), education (a binary indicating if the individual graduated from high school), and age. In theory, for our sample of unmarried women, our coefficients of interest may be significant if the EITC causes any differential selection into marital status by one of these variables. For example, since the EITC disproportionately assists low income individuals, and may reduce the incentive to marry for financial security, we could expect to find a negative impact of the EITC on high school graduation for single women. For the pooled sample of women, however, no such selection issue exists.

In order to handle these possibilities, we run regressions for each of the three placebo outcomes on the main sample of single women (Table 15) and the pooled sample of both married and unmarried women (Table 16). These tests detect one failure, uncovering a significant positive "effect" of the EITC on the age of single mothers. One could take three possible conclusions from this result. First, one could conclude that there is some evidence of the EITC causing differential selection into marriage by age. Second, one could conclude that this provides evidence of spurious correlation in our bunching variable, or third, we could dismiss the result as a bad draw under the null hypothesis. Given that this is the only "failure" of twelve placebo tests that we have conducted jointly, our conclusion is that there is fairly convincing evidence that our main results are not driven by a violation of our identifying assumptions. However, we present these results to the reader in order for them to able to draw their own conclusions.

3 Model

We previously showed that employment, multiple job holding, and job-to-job transitions respond positively to awareness of the EITC. As already mentioned, the latter two margin of responses do not match the predictions of the neoclassical model. Instead, we develop a dynamic search model with hours constraints, on-the-job search, and multiple job holding, that is consistent with the empirical evidence in Section 2.

3.1 Bunching as a Hidden Markov Model

In order to bring structure to our regression results, we must specify the relationship between the county-level bunching measure and individual awareness. In order to get some traction on the problem, we will make two assumptions:

1. Zero bunching implies that there is no local knowledge of the EITC.

2. An increase in local knowledge results in a proportional increase in bunching.

While the former is a reasonable restriction, the latter is a strong parametric (linear) restriction on the relationship between awareness and bunching. Finally, since the research design in our first stage allows for some latent relationship between the level of county bunching and economic outcomes, we build county-level heterogeneity into the bunching measure. Putting this together, we arrive at the measurement equation:

$$\log(B_{ct}) = \kappa_{\tau(c)} + \log(P_{ct}) + \epsilon_{ct},\ \ \epsilon_{ct} \sim \mathcal{N}(0, \sigma_m) \tag{6}$$

where $\tau(c) \in \{1, 2, ..., N_c\}$ is county type, P_{ct} is the fraction of individuals in the county who are aware of the EITC, and ϵ_{ct} is independently distributed noise in the measurement equation. P_{ct} evolves as a Markov process on a Q-sized grid of awareness levels: $1/Q, 2/Q, ..., 1$. Each period, with probability π, a fraction $1/Q$ of individuals in county c will become aware of the EITC, until the county reaches full awareness.

Using the annual bunching data for each county from 2000 to 2009, the parameters $\pi, \kappa_\tau, \sigma_m$, along with the initial distribution of P_{c0} for each type, $\pi_{\tau,0}$, can be estimated by maximum likelihood using the Expectation-Maximization (EM) algorithm. Details and estimates are provided in Appendix C. We use the hidden markov model as a direct input into the simulations we perform when estimating the model.

3.2 Model of Search Frictions

In this subsection we develop a dynamic search model with hours constraints, on-the-job search, and multiple job holding. The framework can be thought of as an extension of the job search model of hours constraints in Bloemen (2008), and in most respects follows the basic partial equilibrium structure introduced by McCall (1970).

In adopting this setup, we combine two labor market features that are known to be critical in matching different properties of available data. In the case of search frictions, many researchers have noted (Mortensen and Pissarides, 1999) that these models simply provide a more intuitively realistic view of the labor market, admitting a more natural interpretation of panel data on employment transitions, wages, and spell durations (Mortensen, 1986; Flinn and Heckman, 1982). In the case of hours constraints, prior work has shown, using a variety of empirical strategies, that they are likely to be an important feature of labor markets (Kahn and Lang, 1991; Altonji and Paxson, 1988; Paxson and Sicherman, 1996), and especially important for understanding the response to tax incentives at the intensive margin (Blundell, Brewer and Francesconi, 2008; Chetty et al., 2011).

While there are not many dynamic models of multiple job holding and hours constraints, other examples include Paxson and Sicherman (1996) and Lalé (2019). Of these, the model introduced by Lalé (2019) is most relevant as the only other environment that combines, to our knowledge, multiple job holding, hours constraints, and search frictions. However, experienced readers will note that the problem is identical to that of a unitary household with two working individuals. In this sense, the model's properties are also informed by analysis of household search models, such as those explored by Guler, Guvenen and Violante (2012) and Flabbi and Mabli (2018).

Time is continuous, and the economy is populated by a continuum of heterogeneous and infinitely-lived workers, who maximize the discounted stream of their expected lifetime utility. We abstract from modeling fertility and marriage decisions. Consistent with the analysis in Section 2, we focus on single women and fertility is taken as a fixed exogenous state. There are K observed types of agents in the economy. Individuals also differ by family size, f, and whether they are aware of the EITC or not, $a = \{0, 1\}$. EITC awareness is driven by the exogenous markov process estimated in the first stage. When $a = 0$, individuals are not aware either of the tax nor of the possibility of becoming aware, and so the problem can be written as if the tax does not exist.

Workers discount future payoffs with factor r and derive flow utility from their consumption, c, and the total number of hours worked, h:

$$u_{k,f,a}(c,h) = \frac{c^{1-\sigma}}{1-\sigma} - \alpha_{k,f}\frac{h^{1+\gamma}}{1+\gamma}$$

where γ is the inverse of the Frisch elasticity of labour supply. For unemployed workers, consumption consists of monthly benefits b. For employed workers, consumption consists of monthly labor income minus federal taxes $T_{f,a}$. Federal taxes include standard deductions, exemptions, and the corresponding EITC, and they are a function of labor income, number of kids, and awareness.[10] Only individuals who are aware of the EITC are subject to tax credits.

Individuals can hold up to two jobs at any one time. Workers find jobs at a rate λ, which differs by observed type and working status (i.e., unemployed, employed at a single job, employed at multiple jobs7). A job offer consists of an hourly wage rate w and a monthly amount of working hours h. Hours offers are modeled with a discrete distribution function: with probability $\rho_k(h)$, the job offer corresponds to a job with h monthly hours. Workers draw wages from a distribution $F_{h,k}$, which is type and hour-specific. Jobs are exogenously terminated at a rate δ, which differs by observed type.

The value function for a worker of type k, family size f, and EITC awareness a, holding two jobs, with hourly wages $\{w_1, w_2\}$ and monthly hours $\{h_1, h_2\}$, is:

$$\begin{aligned}(r+2\delta_k)V^{ee}_{k,f,a}(w_1,h_1,w_2,h_2) \quad = \quad & u_{k,f,a}(c,h) \\ & +\delta_k \max[U_{k,f,a}; V^{e}_{k,f,a}(w_1,h_1)] \\ & +\delta_k \max[U_{k,f,a}; V^{e}_{k,f,a}(w_2,h_2)]\end{aligned} \tag{7}$$

[10] Total federal taxes $T_{f,a}$ are: $T_{f,a} = 0.15\max\{E - D - e_f, 0\} - aEITC(E,f)$, where E is monthly earnings, D is the standard deduction, and e is the personal exemption.

where consumption is the sum of monthly labor income at each job minus federal taxes, $c = w_1h_1 + w_2h_2 - T_{f,a}(w_1, w_2, h_1, h_2)$, and hours are the sum of monthly hours across the two jobs, $h = h_1 + h_2$. The last two terms in equation (7) are the change in the continuation value realized when one job is exogenously terminated, which occurs at a rate δ_k.

When a worker of type k, family size f, and EITC awareness a, holds just one job, with hourly wage w_1 and monthly hours h_1, the value function is:

$$\begin{aligned}(r + \delta_k + \lambda_k^e)V^e_{k,f,a}(w_1, h_1) \quad = \quad & u_{k,f,a}(c, h_1) + \delta_k U_{k,f,a} \\ & + \lambda_k^e \sum_{h'} \rho_k(h') \int \max[V^e_{k,f,a}(w_1, h_1); V^e_{k,f,a}(x, h'); \\ & \qquad V^{ee}_{k,f,a}(w_1, h_1, x, h')] dF_{h',k}(x)\end{aligned} \tag{8}$$

where consumption is the monthly labor income minus federal taxes, $c = w_1h_1 - T_{f,a}(w_1, h_1)$. The last term in equation (8) is the expected increase in the continuation value realized when the worker faces a new job offer, which occurs at a rate λ_k^e. The individual can either reject the offer, accept the offer and quit the current job, or accept the offer and hold the two jobs simultaneously.

Lastly, the value function for an unemployed individual of type k, family size f, and EITC awareness a, is:

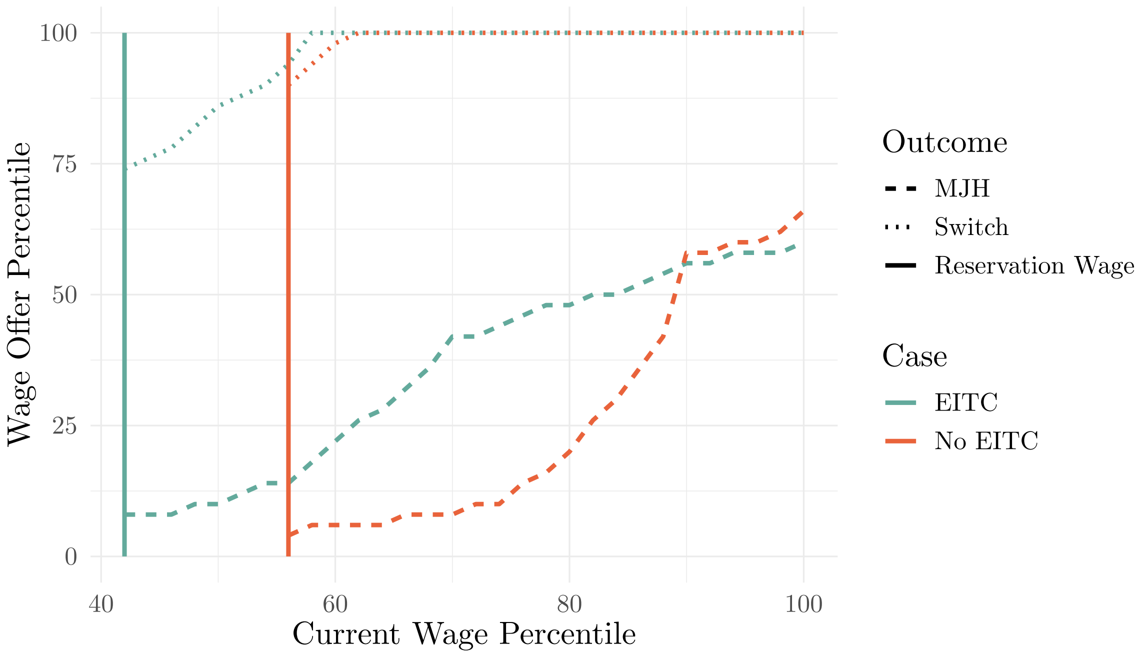
$$(r + \lambda_k^u)U_{k,f,a} = u_{k,f,a}(b, 0) + \lambda_k^u \sum_{h'} \rho_k(h') \int \max[U_{k,f,a}; V^e_{k,f,a}(x, h')] dF_{h',k}(x) \tag{9}$$

where the last term is the expected increase in the continuation value realized when the worker faces a job offer, which occurs at a rate λ_k^u.

3.3 Reservation Wages and MJH

The model offers a set of reservation wage thresholds, defining the point at which unemployed workers accept jobs, at which employed workers switch to new jobs, and at which employed workers accept second jobs. To illustrate, Figure 1 shows the reservation wage strategies for a Type 1 agent who is currently working part-time, and receives another part-time offer. We plot reservation wages before and after the introduction of the EITC. To interpret this graph, note that the vertical solid line is the reservation wage out of unemployment, and shows that in steady state we will not see part-time workers with one job with wages below this point. The lower dashed line is the threshold below which the worker will reject all part-time offers, and above which the offer will be accepted as a second job. We call this the “MJH” threshold, and it is (naturally) increasing in the wage of the current job: the higher the current wage, the less incentive there is to accept additional work. Next, there is a point at which the offered wage is sufficiently high that it is preferable to quit the current job and switch. We call this the “switch” threshold and is given by the dotted line in the graph. In this case, the "switch" threshold is quite high, however this is quite dependent on preferences and the hours combination being considered. There are combinations of parameters such that this point lies below the MJH threshold, in which case there are never transitions into MJH for this employment state.

Figure 1: Reservation Wages



This figure depicts reservation wages for Type 1 individuals who are working part time and receive another part-time offer. The individual rejects offers below the "MJH" reservation wage, and accepts the offer as a second job when the offer lies between this reservation wage and the "Switch" cutoff. For offers above the "Switch" cutoff, she switches to the new job only.

Next, observe that the effect of the EITC is to lower the reservation wage out of unemployment, and to shift up the threshold at which second jobs are accepted, since for these individuals post-tax earnings are higher, and the income effect decreases the incentive to work more. Off-setting this effect is the new range of part-time wages that are acceptable to the worker, creating new opportunities for jobs to be combined. The overall effect, as we will see below, is for the rate of MJH to increase in response to the tax.

3.4 Identification and Estimation Procedure

Our primary data source are the IPUMS' monthly CPS file extracts described in Section 2.2. We further restrict the sample to single women with less than a Bachelor degree. We use 3 observed types ($K = 3$) that are a function of age. Types 1, 2, and 3, are individuals younger than 30 years old, between 31 and 40 years old, and older than 40 years old, respectively.

We make some key functional form assumptions. Following the results in Flinn and Heckman (1982), we assume a recoverable distribution for all the wage offer distributions: a log normal distribution with mean μ_w and variance σ_w. We discretize the choice set of the intensive margin of the labor supply to part-time work and full-time work, $h = \{20, 40\}$. The mean wage offer is allowed to vary by type and hours requirements ($\mu_{w_{h,k}}$). We assume that the ratio between average wage offered for a part-time relative to a full-time job is constant across types (i.e., $\mu_{w_{20,1}}/\mu_{w_{40,1}} = \mu_{w_{20,2}}/\mu_{w_{40,2}} = \mu_{w_{20,3}}/\mu_{w_{40,3}} = \Delta\mu_{w,pt}$). The variance of the wage offer distribution is constant across types and hours requirements. Lastly, the disutility of working hours is allowed to vary by type and family size. Namely, the disutility for an individual of type k and family size f is $\alpha_{k,f} = \alpha_k + \alpha_{f=2+}\mathbf{1}\{f = 2+\}$.

We denote the set of structural parameters that characterize the partial equilibrium model by Ω. The estimation procedure consists of two steps. We begin by estimating the parameters from the Hidden Markov Model, Ω_1. In a second step, we treat the estimates of the Hidden Markov Model as fixed and utilize them to estimate the rest of the parameters, Ω_2.

The set of parameters Ω_2 are estimated via indirect inference (Gourieroux, Monfort and Renault, 1993). The indirect inference estimate minimizes the difference between the observed data and the model-based data from the angle of an auxiliary model. The auxiliary model consists of a set of sample statistics that capture the main features of the structural model. Let g_N represent the vector of sample statistics from the data set, where the N subscript denotes the sample size. Let $g(\Omega)$ represent the vector of model-based analogs of the sample statistics. The indirect inference estimator based on a sample of size N and the selected sample statistics is defined by

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

where W is a positive-definite weighting matrix. In practice, we use the inverse of a diagonal matrix, where the ith component of the diagonal equals the variance of the ith component of g_N.

We choose the sample statistics for the auxiliary model by discussing the identification strategy. The complete list of sample statistics are reported in Table 17. Since nearly all of the parameters are either type-specific or family size-specific, we compute most of the sample statistics separately by age and family size. Some exceptions include the mean log wage for part-time and full-time workers and the moments pertaining to the log wage change distributions, since both the ratio of average full-time to average part-time hourly wages and the variance of the wage distributions are constant across types and family size.

We use a total of 36 sample statistics that can be arranged in three groups. The first group contains transition probabilities between labor market states and the share of workers in each labor market state. Estimation of mobility parameters $(\lambda_k^u, \lambda_k^e, \delta_k, \rho_k)$ is simple using employment and transition data, following the results in Flinn and Heckman (1982). We use the employment rates, the employment-to-unemployment transition rates, and the job-to-job transition rates by type and family size. These moments are linked to the contact rate in unemployment, λ_k^u, the contact rate in employment, λ_k^e, and the job-destruction rate, δ_k. We also target the share of full-time employment, which helps to identify the fraction of full-time offers, ρ_k. We add as a fifth statistic the share of multiple job-holders. Since the disutility of working hours, $\alpha_{k,f}$, represents the preference for work with respect to leisure, this is also identified by the statistics pertaining to labor supply decisions.

The second group of statistics corresponds to the distribution of accepted wages. The parameters of the wage offer distributions $(\mu_{w_{ft,k}}, \Delta\mu_{w,pt}, \sigma_w\ )$ are identified from information on accepted wages once we have assumed recoverable wage offer distributions. Because we observe accepted wage distributions by hours and observed type, the identification strategy can be extended to recover the parameters from the wage offer distributions by type and hours. We consequently use the mean log wage separately by type and hours to identify $\mu_{w_{ft,k}}$ and $\Delta\mu_{w,pt}$. We add the 25th, 50th, and 75th percentile of the log wage change distribution, which helps to identify the variance of the wage offer distribution, σ_w. We target the change in log wages as a strategy to net out potential permanent differences in productivity among individuals within our age categories.

The third group of statistics are the coefficients from the EITC sharp bunching regressions discussed in Section 2.3. The risk aversion parameter, σ, and the inverse of the Frisch elasticity of labour supply, γ, are identified by the dependence of the labor market status on the labor market conditions, depicted by changes in the EITC schedule.

3.5 Model Estimates

In this section, we present the model estimates. We begin by discussing the fit of the model. To this end, we examine the sample statistics we explicitly target in the estimation procedure. The sample statistics from the data and the model are presented in Table 17. The model does a very good job in fitting the transition probabilities between labor market states and the share of workers in each labor market state, with only a few discrepancies for some of the lower probability transitions, such as the job-to-job transitions for individuals between 31 and 40 years old. The model also does quite a good job of matching the distribution of accepted wages, except for the quartiles of the log wage change distributions. Lastly, the model fits well the coefficients from the EITC sharp bunching regressions that were added to identify the preference parameters.

The model estimates are presented in Table 3. The first thing to notice is the variation in the contact rates among the unemployed across age groups. Whereas the unemployment contact rate is estimated to be 0.279 for the below-30 age group, the estimates for the two age groups above 30 are 0.217 and 0.236. Nevertheless, the estimated contact rates are not significantly different from each other. Consistent with the literature, the

Table 3: Parameter Estimates

Parameter	Estimate	Parameter	Estimate
λ_1^u	0.279	λ_1^e	0.098
	[0.191;0.322]		[0.051;0.166]
λ_2^u	0.217	λ_2^e	0.117
	[0.188;0.310]		[0.069;0.145]
λ_3^u	0.236	λ_3^e	0.136
	[0.185;0.312]		[0.086;0.177]
ρ_1	0.334	δ_1	0.103
	[0.221;0.420]		[0.062;0.127]
ρ_2	0.273	δ_2	0.034
	[0.151;0.425]		[0.027;0.055]
ρ_3	0.239	δ_3	0.032
	[0.159;0.416]		[0.022;0.041]
$\mu_{w_{ft},1}$	1.871	$\mu_{w_{ft},3}$	1.864
	[1.698;1.892]		[1.764;1.933]
$\mu_{w_{ft},2}$	1.872		
	[1.699;1.933]		
σ_w	0.288	$\Delta\ \mu_{w,pt}$	0.311
	[0.274;0.332]		[0.180;0.363]
σ	1.948	γ	2.383
	[1.877;2.128]		[1.499;3.434]
α_1	0.050	α_3	0.021
	[0.013;0.087]		[0.004;0.043]
α_2	0.015	$\Delta\ \alpha_{f=2+}$	0.011
	[0.006;0.045]		[0.002;0.017]

95% bootstrap confidence interval in parentheses. Types 1, 2, and 3 correspond to single women younger than 30, between 31 and 40 years old, and older than 40, respectively.

contact rates among the unemployed are twice as large as the contact rates among the employed. This indicates, for example, that contacts occur every 4.6 months on average when unemployed and every 8.5 months on average when employed, for the mid-age group. The estimates of ρ_k imply that 23% to 33% of the job offers from unemployment and employment correspond to part-time offers, with no significant variation across age groups. The estimated exogenous job destruction rates are approximately three-times smaller than the contact rates in the employment states for the two highest age groups, and roughly similar for the lowest age group. This means that employment spells are more likely to end in unemployment for single women younger than 30 relative to older women.

The estimates from the wage distributions suggest that full-time jobs offer hourly wages that are, on average, three times larger than those offered by part-time jobs. The average hourly wage offered for a part-time job is estimated to be 6.5 dollars. Perhaps a bit surprisingly, there is no significant variation in average offered wages across age groups. One explanation for our finding is that we narrow our analysis to low-educated single women. The estimated variance for the wage distribution is 0.29.

As expected, the estimates of α_k and $\Delta\alpha_{f=2+}$ imply that the disutility of working hours increases with family size and decreases with age. Lastly, the estimate of γ implies a Frisch elasticity of labour supply of 0.42, which is within the range estimated in the literature.

4 Analysis

Having estimated the model, which maps the results from our research design to a set of key structural parameters, we can now use the model for two purposes. The first purpose is to examine the quantitative implications of the two key frictions for positive and normative analysis. Our framework enables us to evaluate both short term and long term effects on labor supply, pertaining both to the extensive and intensive response margins. The second purpose is to examine the welfare impact of the EITC.

4.1 Dynamic Impacts of the Tax Credit

We perform a counterfactual that simulates the introduction of the EITC, taking the tax program parameters from 2005. While our research design exploited regional variation in awareness of the EITC over time, one can interpret the effects here as either an individual becoming aware, or the policy being introduced to an individual who is already fully aware. The three labor outcomes that we focus on are employment, multiple job holding, and job-to-job transitions.[11] We evaluate the effects of the EITC in the short run - i.e., 6 and 12 months after its introduction - and in the long run - i.e., 2,3, and 8 years after its introduction.

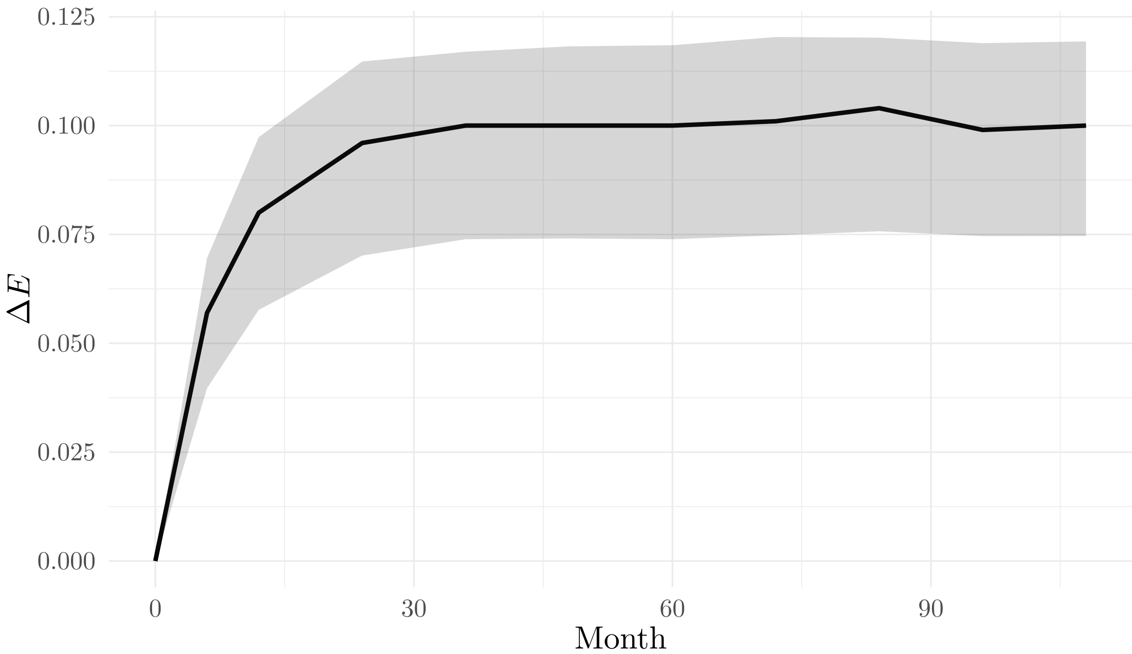
[11]We do not discuss the implications on working hours since the model only allows for two hours arrangements. A model with continuous hours would be more appropriate to study the effects of the EITC on working hours.

Table 4: Dynamic Impacts of EITC

	Months Elapsed					
	6	12	24	36	48	96
	percentage points (pp)					
Δ Employment	5.71	8.01	9.57	9.99	10.02	9.90
	[3.97;6.96]	[5.77;9.74]	[7.02;11.47]	[7.39;11.70]	[7.41;11.82]	[7.46;11.89]
Type 1	4.56	5.75	5.86	5.85	6.08	5.82
	[0.32;9.41]	[0.39;12.25]	[0.42;13.12]	[0.48;13.38]	[0.50;13.57]	[0.30;13.27]
Type 2	6.78	9.72	11.91	12.52	12.34	12.35
	[4.36;7.62]	[6.03;10.40]	[7.23;12.08]	[7.44;12.69]	[7.72;12.76]	[7.36;12.80]
Type 3	5.82	8.59	10.91	11.56	11.61	11.48
	[4.39;6.66]	[7.04;9.62]	[9.46;11.35]	[9.96;11.98]	[10.04;12.20]	[10.25;12.27]
Δ MJH	0.09	0.36	0.99	1.31	1.58	1.86
	[-0.07;0.25]	[0.06;0.65]	[0.42;1.25]	[0.74;1.57]	[0.90;1.87]	[1.05;2.17]
Type 1	-0.06	0.10	0.46	0.50	0.51	0.40
	[-0.21;0.50]	[-0.22;1.12]	[-0.04;1.63]	[-0.04;1.83]	[-0.01;1.84]	[0.02;1.98]
Type 2	0.12	0.43	1.13	1.51	1.86	2.17
	[-0.12;0.30]	[-0.03;0.90]	[0.15;1.73]	[0.25;2.21]	[0.38;2.53]	[0.56;3.00]
Type 3	0.19	0.54	1.34	1.87	2.31	2.94
	[-0.09;0.32]	[0.00;0.89]	[0.40;1.87]	[0.68;2.54]	[0.90;2.86]	[1.39;3.38]
Δ J2J	0.42	0.50	0.64	0.60	0.65	0.64
	[0.21;0.54]	[0.24;0.65]	[0.32;0.73]	[0.28;0.83]	[0.33;0.78]	[0.30;0.80]
Type 1	0.49	0.57	0.78	0.75	0.68	0.74
	[0.07;0.87]	[0.02;1.04]	[0.02;1.09]	[-0.04;1.34]	[0.03;1.26]	[-0.06;1.18]
Type 2	0.37	0.55	0.57	0.60	0.73	0.72
	[0.18;0.59]	[0.26;0.79]	[0.34;0.89]	[0.25;0.90]	[0.27;0.92]	[0.31;0.95]
Type 3	0.42	0.42	0.63	0.55	0.62	0.55
	[0.18;0.51]	[0.22;0.67]	[0.25;0.69]	[0.28;0.82]	[0.33;0.89]	[0.31;0.79]

95% bootstrap confidence interval in parentheses. Types 1, 2, and 3 correspond to single women younger than 30, between 31 and 40 years old, and older than 40, respectively.

Figure 2: EITC: Employment Impacts



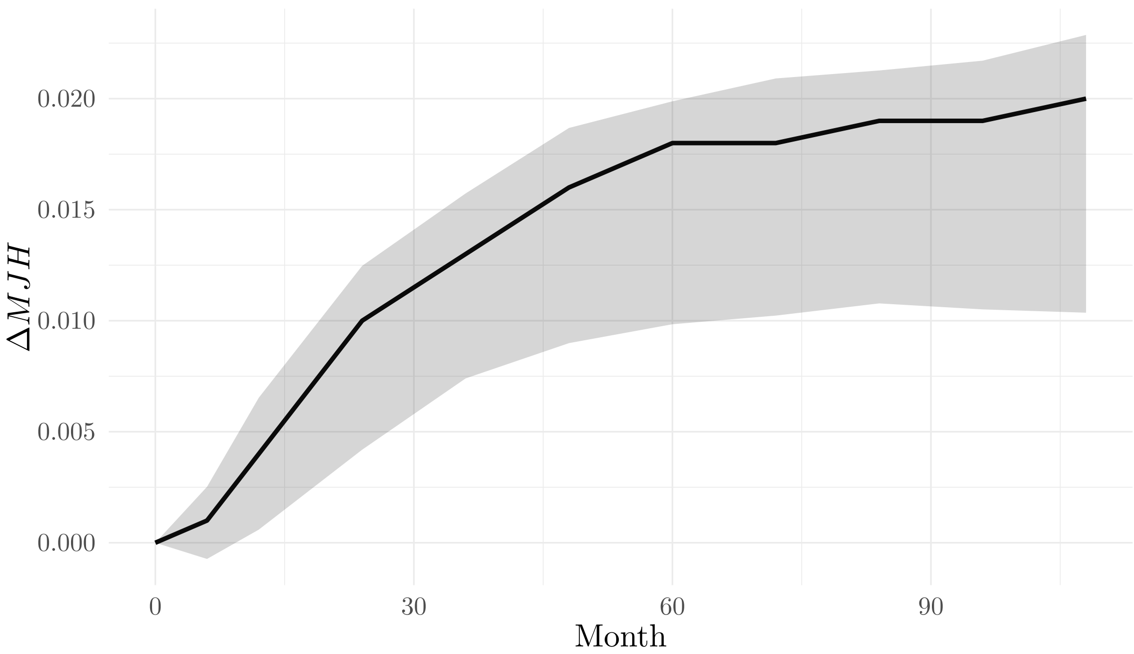
This figure shows the dynamic impact of the introduction of the EITC on employment, as simulated by our estimated model. Shaded region indicates the 95% confidence interval, estimated using the bootstrapped sample.

Table 4 shows the dynamic impacts of the EITC on labor supply outcomes. For ease of interpretation, we also display these results graphically in Figures 2 through 4.

The first thing to notice is that employment increases by 5.7 and 8.0 percentage points, on average, in the first 6 and 12 months after the implementation of the EITC, respectively. The growing trend in employment persists in the following years, reaching a 9.9 percentage point increase after 8 years. All three age-types see significant increases in employment, with younger types experiencing smaller increases. This finding is consistent with the literature studying the effect of the EITC on employment (Eissa and Liebman, 1996; Meyer and Rosenbaum, 2001; Grogger, 2003; Hotz and Scholz, 2006). A quite novel result is that short-term responses reflect only part of the overall effect of the EITC on employment. Thus, our relatively standard model of search frictions predicts that empirical studies of contemporaneous responses to the EITC will underestimate the long-run impact of the policy.

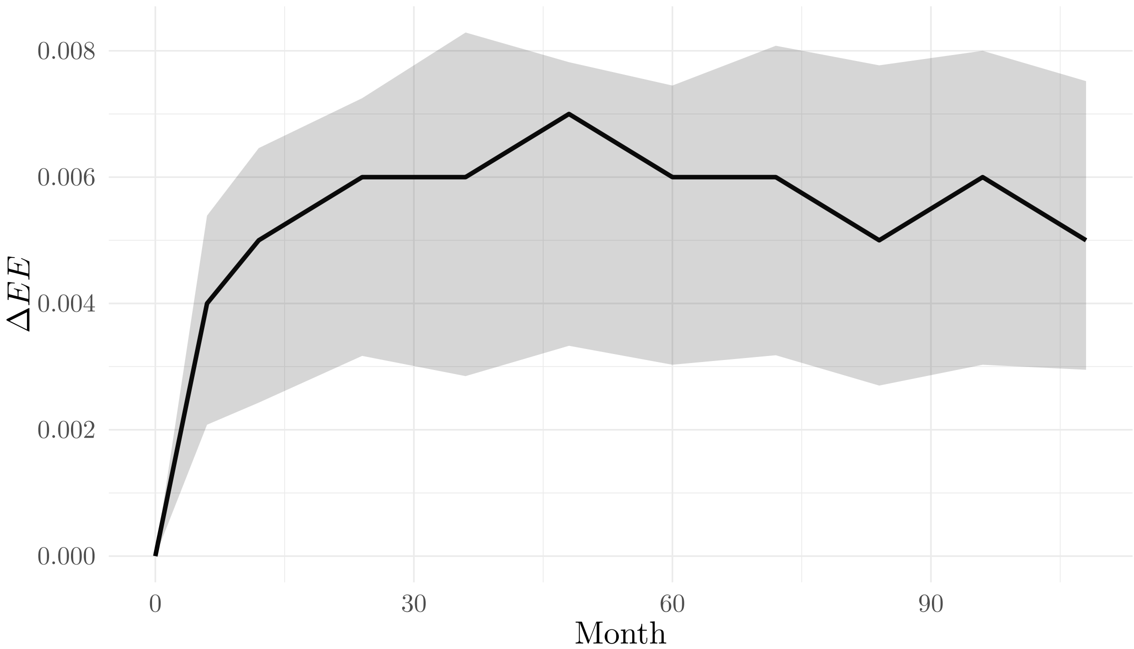
We also document intensive margin responses to the EITC. While multiple job holding stays relatively flat the first year after the policy, it increases 1.9 percentage points, on average, 8 years later. In line with extensive margin responses, younger women expe-

Figure 3: EITC: Impact on Multiple Job Holding



This figure shows the dynamic impact of the introduction of the EITC on multiple job holding, as simulated by our estimated model. Shaded region indicates the 95% confidence interval, estimated using the bootstrapped sample.

Figure 4: EITC: Impact on Employer-Employer Transitions



This figure shows the dynamic impact of the introduction of the EITC on employer-employer transitions, as simulated by our estimated model. Shaded region indicates the 95% confidence interval, estimated using the bootstrapped sample.

rience only a small increase in multiple job holding relative to the older types. We also observe a significant increase in job-to-job transitions as a result of the policy. Job-to-job transitions increase by 0.4 percentage points 6 months after the policy, and remain stable in the next 8 years. These findings are in line with our hypothesis that workers facing hours constraints can take new jobs and/or second jobs that better suit their preferences over the intensive margin, in response to tax changes.

Interpretation of these dynamic impacts is quite straightforward. While the changes in incentives induced by the introduction of the EITC are immediate, search frictions and hours constraints inhibit adjustments to these incentives, and the timing of these adjustments is determined by the contact rates λ^u and λ^e. As one example, notice that estimated contact rates out of unemployment for Type 1 mothers (λ_1^u) are larger than for Types 2 and 3. Consequently, there is a much smaller discrepancy between the short and long run impacts of the tax on employment for Type 1 individuals. Clearly, an important lesson from this exercise is that the severity of search frictions in a particular market will critically determine researchers' ability to infer steady-state policy elasticities from common research designs.

4.2 Welfare Analysis

How do the empirical implications of frictions in our model carry over to inference on welfare? There are several issues to discuss, relating to (1) comparisons of inference with the frictionless benchmark, (2) dynamic and heterogeneous impacts on welfare inside the model, and (3) the contribution of frictions to the insurance value of the tax. We will address these issues in corresponding order.

4.2.1 Comparison with Classic Formulae

The paradigmatic approach to normative analysis of tax policy, as exemplified by Eissa, Kleven and Kreiner (2008) in the case of the EITC, is to assess the effect of the policy change on total deadweight loss imposed by taxes in a perfectly competitive economy. Under the frictionless market assumption, these effects can be phrased in terms of behavioral elasticities. In particular, Eissa, Kleven and Kreiner (2008) derive a formula in which the welfare effect is a linear function of the extensive and intensive marginal elasticity, with the former being larger in magnitude and driving welfare results. Since we estimate that long run employment effects are between 24% and 73% larger[12] than the short run, this implies that a researcher using this formula would under-estimate welfare gains by the same amount (24 to 73 percent).

4.2.2 A Formula for Welfare Analysis

Ultimately, however, there is no direct relationship between classic deadweight loss formulae and our structural estimates of welfare gains. As opposed to the static frictionless case, agents in our model face idiosyncratic income risk through exogenous separations, uncertain search outcomes, and stochastic wage draws. Therefore, in addition to the direct value of the transfer, the tax credit also provides some insurance value through a decrease in the dispersion of post-tax wage draws.

In order to organize this discussion, we first derive a formula for welfare gains from tax changes that decomposes the reform into these two effects. We begin by discretizing the problem into N states, with each state corresponding to an employment arrangement and a wage. Let $\tau \in \mathbb{R}^N$ summarise the direction of a tax reform, such that the change in post-tax income in state i, y_i, can be written as:

$$dy_i = \tau_i d\gamma$$

where γ dictates the intensity of the reform. Here we consider the change in welfare with respect to a *marginal reform.* In Appendix D we show that the marginal change in welfare for an agent in state i can be written as:

$$\left.\frac{drV_i}{d\gamma}\right|_{\gamma=0} = \sum_{j=1}^{N} \omega_{i,j} u'_j \tau_j$$

[12] The exact percentage depends on whether we use the 6 or 12 month effect as the short run benchmark.

where u'_j is the marginal utility of consumption in state j, the vector ω_i sums to one, and can be treated as a probability vector, such that:

$$\left.\frac{drV_i}{d\gamma}\right|_{\gamma=0} = \mathbb{E}_{\omega,i}[\tau]\mathbb{E}_{\omega,i}[u'] + \mathbb{C}_{\omega,i}[u'\tau]. \tag{10}$$

This formula contains the usual logic on first order welfare effects, where behavioral responses to the tax can be ignored. The weight $\omega_{i,j}$ summarizes the relevance of state j for an agent in state i, which is determined by the rate at which they discount the future, as well as the risk of state j's arrival, and the expected duration of that state.[13]

We refer to the first term in Equation (10) as the *incidence effect*, which summarizes the direct consumption value of the transfer, as weighted by the agent's probability measure ω_i, and scaled by the mean utility of consumption. It takes into account the dynamics of the system, not just the current state. We refer to the second term in Equation (10) as the *insurance effect*, given by the covariance between the marginal utility of consumption in a state and the relative generosity of the transfer in that state. It takes into account that the transfer may be more valuable in states where marginal utility is higher, and weights them by their relevance for the agent's current discounted present value. In order to convert the decomposition in (10) into a money metric, we divide both sides by the mean marginal utility of consumption:

$$\left.\frac{drV_i}{d\gamma}\right|_{\gamma=0} \Big/ \mathbb{E}_{\omega,i}[u'] = \mathbb{E}_{\omega,i}[\tau] + \frac{\mathbb{C}_{\omega,i}[u'\tau]}{\mathbb{E}_{\omega,i}[u']}. \tag{11}$$

4.2.3 Welfare Impacts of the EITC

We evaluate the welfare gain from the EITC by simulating its introduction and calculating a consumption equivalent measure of welfare: the permanent percentage change in consumption that would deliver an equivalent percentage increase in welfare. These results are reported in Table 5. Using the welfare formula in Equation 10 to guide our analysis, our interest is focused on the timing of welfare gains as they relate to the timing of frictional adjustments, and the distribution of welfare gains across types and employment states.

We find that even though behavioral responses vary significantly over the time horizon, average welfare gains stay remarkably flat in the short term and long term, implying that despite frictions, the gains from the tax are internalized immediately in dynamic values. One exception to this is observed, however, in the welfare impacts for those who were unemployed at the time the policy was implemented. In this case we see small but relevant dynamics in welfare impacts for Types 2 and 3, implying that frictions to adjustment do have an effect on welfare gains for some individuals.

One clear pattern is that Type 1 (i.e. younger) individuals enjoy much larger welfare gains from the introduction of the credit than Types 2 and 3. This can be rationalized by a combination of incidence and insurance. To see this, we begin by noting that Type

[13] Further intuition for the weights is developed in Appendix D.

Table 5: Welfare Gains from EITC

	Months Elapsed					
	6	12	24	36	48	96
Type 1	8.61	8.61	8.61	8.61	8.61	8.61
	[1.19;15.32]	[1.20;15.33]	[1.20;15.33]	[1.20;15.33]	[1.20;15.33]	[1.20;15.34]
Type 2	2.09	2.10	2.11	2.11	2.11	2.10
	[1.65;5.42]	[1.66;5.43]	[1.66;5.43]	[1.66;5.44]	[1.66;5.44]	[1.66;5.44]
Type 3	1.83	1.84	1.86	1.86	1.86	1.86
	[1.44;2.75]	[1.46;2.75]	[1.46;2.76]	[1.46;2.75]	[1.45;2.76]	[1.45;2.75]
Type 1 - Unemployed	8.65	8.65	8.66	8.65	8.66	8.66
	[1.17;15.36]	[1.20;15.36]	[1.21;15.36]	[1.21;15.36]	[1.22;15.36]	[1.21;15.37]
Type 2 - Unemployed	2.06	2.11	2.14	2.15	2.15	2.15
	[1.59;5.45]	[1.64;5.46]	[1.66;5.47]	[1.67;5.48]	[1.67;5.49]	[1.68;5.50]
Type 3 - Unemployed	1.80	1.86	1.90	1.91	1.91	1.93
	[1.38;2.71]	[1.43;2.77]	[1.46;2.80]	[1.47;2.80]	[1.46;2.80]	[1.48;2.80]
Type 1 - Employed	8.58	8.58	8.57	8.57	8.57	8.57
	[1.22;15.29]	[1.20;15.30]	[1.19;15.31]	[1.18;15.31]	[1.18;15.31]	[1.18;15.31]
Type 2 - Employed	2.12	2.10	2.09	2.08	2.08	2.07
	[1.68;5.41]	[1.67;5.41]	[1.66;5.41]	[1.65;5.41]	[1.65;5.41]	[1.64;5.41]
Type 3 - Employed	1.85	1.84	1.83	1.83	1.83	1.83
	[1.48;2.77]	[1.47;2.74]	[1.46;2.73]	[1.45;2.73]	[1.44;2.73]	[1.43;2.71]
Average	4.14	4.15	4.16	4.16	4.16	4.16
	[1.65;6.74]	[1.66;6.75]	[1.65;6.75]	[1.65;6.75]	[1.65;6.75]	[1.65;6.75]

95% bootstrap confidence interval in parentheses. Types 1, 2, and 3 correspond to single women younger than 30, between 31 and 40 years old, and older than 40, respectively.

1 women face higher rates of job destruction (δ_1) as well as job offers while unemployed (λ_1^u). The former implies that, despite drawing from an almost identical wage offer distribution as the other types, younger women are forced more often into unemployment and to start again at the bottom of the job ladder, leading to lower earnings on average in steady state. These women are, therefore, more likely to benefit based on their average position in the earnings distribution. This is the incidence effect. However, higher mobility rates also imply that younger women face much higher earnings risk, implying that part of the value gained from the EITC can be attributed to the insurance effect.

We conduct two exercises in order to emphasise this point, and the relevance of rate parameters for welfare gains. First, we re-compute welfare gains for Type 1 individuals after setting their mobility parameters to the same values as Type 2 agents. These results are presented in Table 6, which verifies that the discrepancy in welfare gains is eliminated once these key mobility parameters are equalized. This exercise makes an important point: that the welfare impact, and more generally the normative implications, of tax changes depend crucially on the relevance of search frictions for the incident population. Furthermore, these fundamentally dynamic properties of labor markets are obviated in the cross-section. For example, notice that doubling both the job-finding rate as well as the job destruction rate has no effect on steady state unemployment rate, but will increase the willingness to pay for the transfer, since the churning of individuals through states in which the tax is beneficial is much higher.

Next, we use Equation (11) to decompose the welfare gains for each type, with results given in Table 7. To make this calculation, we use the fact that the discount rate r is small in our model compared to mobility rates, and use the steady state distribution as an approximation for the welfare weights, ω.[14] To calculate the direction of the reform, τ, we calculate the implied tax credit given the earnings of each individual in the simulate steady state.

The resulting decomposition offers the following insights. First, the contribution of the insurance effect is an order of magnitude smaller than incidence for all types. Second, Type 1 individuals enjoy larger welfare gains both because of incidence and insurance effects, consistent with our analysis in the previous paragraph. Finally, for Types 2 and 3, we find that the insurance effect is in fact off-setting: transfers are provided in states where marginal utility of consumption is lower than the average (suggesting the existence of a more beneficial transfer shape for these types). Next, we conduct a similar counterfactual to the previous full structural exercise, setting the job finding and job destruction rate parameters for Type 1 individuals equal to those for Type 2. In doing so, we find that this change greatly reduces the incidence of the tax credit for these individuals, while mildly enhancing its insurance value.

One may reasonably argue that the implications for the insurance channel are extreme in our model, since we do not allow for consumption smoothing over time (for example, by allowing the accumulation of a risk-free asset). Still, we find that our model is sufficient to illustrate a relevant mechanism for welfare analysis. Moreover, the ability to self-insure does not discount our observation that frictions are a source of income risk

[14]See Appendx D for details on how this approximation works.

Table 6: Welfare Gains from EITC - Specification with $\delta_1 = \delta_2$ and $\lambda_1^u = \lambda_u^2$

	Months Elapsed					
	6	12	24	36	48	96
Type 1	1.92	1.95	1.97	1.99	2.00	2.00
	[1.51;18.21]	[1.52;18.22]	[1.53;18.23]	[1.53;18.23]	[1.53;18.24]	[1.53;18.24]
Type 2	2.09	2.10	2.11	2.11	2.11	2.10
	[1.65;5.42]	[1.65;5.43]	[1.66;5.43]	[1.66;5.44]	[1.66;5.44]	[1.66;5.44]
Type 3	1.83	1.84	1.86	1.86	1.86	1.86
	[1.44;2.75]	[1.46;2.75]	[1.46;2.76]	[1.46;2.75]	[1.45;2.76]	[1.45;2.75]
Type 1 - Unemployed	1.77	1.86	1.95	2.00	2.03	2.06
	[1.37;18.27]	[1.44;18.24]	[1.52;18.24]	[1.55;18.24]	[1.55;18.26]	[1.56;18.27]
Type 2 - Unemployed	2.06	2.11	2.14	2.15	2.15	2.15
	[1.59;5.45]	[1.64;5.46]	[1.66;5.47]	[1.67;5.48]	[1.67;5.49]	[1.68;5.50]
Type 3 - Unemployed	1.80	1.86	1.90	1.91	1.91	1.93
	[1.38;2.71]	[1.43;2.77]	[1.46;2.80]	[1.47;2.80]	[1.46;2.80]	[1.48;2.80]
Type 1 - Employed	2.23	2.14	2.02	1.96	1.93	1.87
	[1.67;18.19]	[1.63;18.21]	[1.59;18.23]	[1.52;18.23]	[1.5;18.24]	[1.49;18.23]
Type 2 - Employed	2.12	2.10	2.09	2.08	2.08	2.07
	[1.68;5.41]	[1.67;5.41]	[1.66;5.41]	[1.65;5.41]	[1.65;5.41]	[1.64;5.41]
Type 3 - Employed	1.85	1.84	1.83	1.83	1.83	1.83
	[1.48;2.77]	[1.47;2.74]	[1.46;2.73]	[1.45;2.73]	[1.44;2.73]	[1.43;2.71]
Average	1.94	1.96	1.97	1.98	1.98	1.99
	[1.78;7.48]	[1.79;7.48]	[1.80;7.48]	[1.80;7.49]	[1.80;7.48]	[1.80;7.49]

95% bootstrap confidence interval in parentheses. the results in this table refer to a simulation in which Type 1 are endowed with the same contact rates as Type 2. Types 1, 2, and 3 correspond to single women younger than 30, between 31 and 40 years old, and older than 40, respectively.

Table 7: Welfare Decomposition: Contribution of Insurance Effects

	Type 1		Type 2		Type 3	
	Incidence	Insurance	Incidence	Insurance	Incidence	Insurance
Baseline	111.85	16.96	91.00	-12.53	79.25	-2.66
Counterfactual	54.41	21.25	-	-	-	-

This table shows the approximate decomposition of welfare gains from the EITC, as given in the main text, using equation (11), and using the steady state distribution to approximate the weights ω for each type. Results are reported in dollars per month. Numbers are calculated using estimates found in Table 3. "Counterfactual" refers to a simulation in which Type 1 are endowed with the same contact rates as Type 2. No other changes are made.

that more evenly dispurse the incidence of the tax credit across individuals. Taken together, our analysis suggests that accounting for dynamics and search frictions in labor markets adds an additional channel through which the EITC has had positive welfare impacts, which are not summarised in traditional analyses of this reform using the static neoclassical model.

4.3 Negative Income Tax

To further explore the implications of our estimated model parameters, we compare the impacts of the EITC to a universal *Negative Income Tax* (NIT). To perform this analysis, we impose that the new regime incur the same fiscal cost[15] as the EITC used in our prior analysis. We do not provide a complete analysis of optimal redistributive tax policy. In general equilibrium, several interesting issues arise, as the tax code interacts with wage-setting and the optimal posting of vacancies (Hungerbühler et al., 2006) and the intensity and direction of workers' search effort (Golosov, Maziero and Menzio, 2013). Instead we maintain focus on one particular counterfactual as a means to illustrate the implications of the frictions in our model.

The NIT is characterized by two parameters: a tax percentage and an income cutoff, which determines the level at which individuals start paying income tax. Given an income cutoff, we estimate the NIT tax percentage that delivers the same fiscal cost as the EITC. We repeat this procedure for different income cutoffs and select the combination of parameters (i.e., income cutoff and tax percentage) that generates the largest average welfare gain.

Table 8 shows that the NIT has a small but significant negative effect on employment, an ambiguous effect on MJH, and a small, significant effect on the rate of EE transitions. More interestingly, as measured by average consumption equivalence, the NIT is not preferred to the EITC by any of the three types. While we cannot, for reasons discussed previously, make any direct analogy with prior results in the public finance literature, it is worth noting that this finding echoes that of Saez (2002), who shows that optimal nonlinear tax schedules may exhibit negative marginal rates if extensive marginal elasticities are sufficiently high relative to intensive marginal elasticities. This channel is active in our model, in which the participation responses, as measured by the change in reservation wages, dominates the intensive margin: changes to the tax have a relatively small effect on job acceptance decisions for the employed.

In our case, welfare effects will also depend, to a large extent, on the dynamic properties of the tax. Even though marginal utilities are highest in unemployment, our estimated rate parameters imply that agents in the model spend a relatively small amount of time in this state. Abstracting away from behavioral responses, we can return to Equation 10 and compare marginal changes that move in the direction of the NIT against those that resemble a tax credit. Revenue neutrality dictates that incidence should be identical, on average, for both reforms (modulo behavioral responses). However, rate

[15]The fiscal cost is denoted as the simulated sum of unemployment benefits and tax credits minus income tax collections.

Table 8: Welfare Gains from Negative Income Tax

	Months Elapsed	
	12	96
Type 1	2.88	2.88
	[1.57;6.67]	[1.57;6.67]
Type 2	1.86	1.86
	[0.92;3.22]	[0.92;3.22]
Type 3	1.51	1.51
	[0.91;2.61]	[0.91;2.61]
Average	2.07	2.07
	[1.19;3.97]	[1.19;3.97]
Δ Employment	-3.70	-3.63
	[-6.05;-2.07]	[-6.05;-2.07]
Δ MJH	0.09	-0.04
	[-0.34;0.13]	[-0.34;0.13]
Δ J2J	-0.18	-0.16
	[-0.34;-0.04]	[-0.34;-0.04]

95% bootstrap confidence interval in parentheses. Types 1, 2, and 3 correspond to single women younger than 30, between 31 and 40 years old, and older than 40, respectively. The Negative Income Tax is simulated such that it achieves the same fiscal cost as the Earned Income Tax Credit.

parameters deliver weights, Ω, such that agents prefer to be insured against low-wage draws rather than unemployment. Thus, the overall effect is that individuals in the model prefer the EITC to a revenue equivalent NIT. However, given that we found negative insurance effects for Type 2 and 3 agents in the previous section, it is clear that further welfare gains are possible from a more sophisticated non-linear adjustment to the tax schedule. We leave further exploration of this issue to future research.

5 Conclusion

In this paper we have taken the stance that tax policy analysis can be enhanced by taking into consideration hours constraints and search frictions in labor markets. We see this not just in the model's ability to rationalize new evidence on the response to the EITC, but also in the ensuing implications for measurement and policy. We believe that this extension has offered new and relevant insights for the design and analysis of taxes and transfers.

However, in order to advance this approach we have adopted some clear limitations. We conclude by acknowledging the most important of these. First and foremost, we do not consider even partial equilibrium adjustments in wages, as in Rothstein (2010) and Hungerbühler et al. (2006), nor do we consider general equilibrium effects of policies on job creation. Furthermore, 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 mothers. 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. Second, we do not allow for self-insurance through savings. This creates somewhat stark implications for the insurance implications of tax reforms, and it would certainly be interesting to account for this by considering the consumption response to job switches, for example. Finally, our model does not consider endogenous search intensity, which creates an additional margin of adjustment that could affect both the speed of adjusment 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).

Nevertheless, we feel that however much these additions would moderate the insights we have contributed in this study, they do not negate them, and we therefore leave such extensions to future work.

A Tables

Table 9: EITC Sharp Bunching Regression - All Women, 18-55

	Emp	MJH	J2J
	(1)	(2)	(3)
K	-0.085***	-0.014***	-0.006***
	(0.007)	(0.001)	(0.001)
B	-0.713**	-0.150	-0.126*
	(0.245)	(0.077)	(0.052)
$K \times B$	0.392**	0.199***	0.056**
	(0.133)	(0.037)	(0.021)
county	Yes	Yes	Yes
date	Yes	Yes	Yes
age	Yes	Yes	Yes
educ	Yes	Yes	Yes
race	Yes	Yes	Yes
Estimator	OLS	OLS	OLS
N	1,750,613	1,721,239	794,684
R^2	0.061	0.013	0.006

Columns show results for (1) Employment; (2) Multiple Job Holding; (3) Job-to-Job transitions. Standard errors clustered at the state level. *** stands for p-value<0.01, ** stands for p-value<0.05, * stands for p-value<0.1.

Table 10: EITC Sharp Bunching Regression - Single Women, 18-40

	Emp	MJH	J2J
	(1)	(2)	(3)
K	-0.041***	-0.019***	-0.010***
	(0.005)	(0.002)	(0.002)
B	-1.258***	-0.236**	-0.196**
	(0.278)	(0.090)	(0.070)
$K \times B$	0.591***	0.341***	0.163**
	(0.156)	(0.073)	(0.055)
county	Yes	Yes	Yes
date	Yes	Yes	Yes
educ	Yes	Yes	Yes
age	Yes	Yes	Yes
race	Yes	Yes	Yes
Estimator	OLS	OLS	OLS
N	547,464	538,165	235,989
R^2	0.104	0.018	0.007

Columns show results for (1) Employment; (2) Multiple Job Holding; (3) Job-to-Job transitions. Standard errors clustered at the state level. *** stands for p-value<0.01, ** stands for p-value<0.05, * stands for p-value<0.1.

Table 11: EITC Sharp Bunching Regression - All Women, 18-40

	Emp	MJH	J2J
	(1)	(2)	(3)
K	-0.147***	-0.025***	-0.011***
	(0.007)	(0.002)	(0.001)
B	-1.271***	-0.233**	-0.119
	(0.297)	(0.073)	(0.075)
$K \times B$	0.722***	0.363***	0.106**
	(0.134)	(0.061)	(0.033)
county	Yes	Yes	Yes
date	Yes	Yes	Yes
educ	Yes	Yes	Yes
age	Yes	Yes	Yes
race	Yes	Yes	Yes
Estimator	OLS	OLS	OLS
N	1,023,241	1,006,286	438,503
R^2	0.076	0.015	0.006

Columns show results for (1) Employment; (2) Multiple Job Holding; (3) Job-to-Job transitions. Standard errors clustered at the state level. *** stands for p-value<0.01, ** stands for p-value<0.05, * stands for p-value<0.1.

Table 12: EITC Sharp Bunching Regression - Total Hours

	Hours			
	(1)	(2)	(3)	(4)
K	-0.488**	-2.598***	-0.018	-2.197***
	(0.160)	(0.211)	(0.262)	(0.292)
B	-14.129*	-20.687**	-13.706	-17.224
	(6.437)	(7.235)	(7.637)	(11.687)
$K \times B$	-5.546	11.427	-13.698	8.382
	(9.128)	(8.086)	(12.659)	(11.972)
county	Yes	Yes	Yes	Yes
date	Yes	Yes	Yes	Yes
age	Yes	Yes	Yes	Yes
educ	Yes	Yes	Yes	Yes
race	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	OLS
N	509,863	1,088,101	341,393	615,435
R^2	0.171	0.087	0.139	0.077

Columns show results for (1) Main Sample; (2) Pooled Sample; (3) Young sample; (4) Young pooled sample. Standard errors clustered at the state level. *** stands for p-value<0.01, ** stands for p-value<0.05, * stands for p-value<0.1.

Table 13: Placebo Regression - Single Women

	Emp	MJH	J2J
	(1)	(2)	(3)
K	-0.038***	-0.019***	-0.007**
	(0.006)	(0.002)	(0.002)
kids3	-0.071***	-0.004	0.000
	(0.008)	(0.003)	(0.003)
B	-0.942***	-0.156	-0.080
	(0.265)	(0.113)	(0.076)
$K \times B$	0.544**	0.325***	0.125*
	(0.172)	(0.069)	(0.060)
$(K \geq 3) \times B$	0.123	0.113	0.024
	(0.202)	(0.088)	(0.121)
county	Yes	Yes	Yes
date	Yes	Yes	Yes
age	Yes	Yes	Yes
educ	Yes	Yes	Yes
race	Yes	Yes	Yes
Estimator	OLS	OLS	OLS
N	483,162	478,722	212,036
R^2	0.105	0.022	0.008

Columns show results for (1) Employment; (2) Multiple Job Holding; (3) Job-to-Job transitions. Standard errors clustered at the state level. *** stands for p-value<0.01, ** stands for p-value<0.05, * stands for p-value<0.1.

Table 14: Placebo Regression - All Women

	Emp	MJH	J2J
	(1)	(2)	(3)
K	-0.138***	-0.027***	-0.008***
	(0.008)	(0.002)	(0.001)
kids3	-0.101***	-0.001	0.002
	(0.007)	(0.002)	(0.001)
B	-0.983**	-0.191*	-0.061
	(0.346)	(0.077)	(0.085)
$K \times B$	0.549***	0.358***	0.077*
	(0.117)	(0.062)	(0.031)
$(K \geq 3) \times B$	0.461	0.058	-0.022
	(0.242)	(0.055)	(0.060)
county	Yes	Yes	Yes
date	Yes	Yes	Yes
age	Yes	Yes	Yes
educ	Yes	Yes	Yes
race	Yes	Yes	Yes
Estimator	OLS	OLS	OLS
N	909,430	901,200	395,489
R^2	0.081	0.017	0.007

Columns show results for (1) Employment; (2) Multiple Job Holding; (3) Job-to-Job transitions. Standard errors clustered at the state level. *** stands for p-value<0.01, ** stands for p-value<0.05, * stands for p-value<0.1.

Table 15: Placebo Regression - Single Women

	Nonwhite	HS	Age
	(1)	(2)	(3)
K	0.099***	0.230***	5.673***
	(0.018)	(0.009)	(0.116)
B	0.283	0.057	-2.350
	(0.353)	(0.304)	(3.820)
$K \times B$	-0.129	0.738	11.043***
	(0.385)	(0.416)	(2.400)
county	Yes	Yes	Yes
date	Yes	Yes	Yes
age	Yes	Yes	
educ	Yes		Yes
race		Yes	Yes
Estimator	OLS	OLS	OLS
N	483,162	483,162	483,162
R^2	0.190	0.228	0.266

Columns show results for (1) a binary variable indicating if the individual is nonwhite, (2) a binary variable indicating if the individual graduated from high school, (3) and age. Standard errors clustered at the state level. *** stands for p-value<0.01, ** stands for p-value<0.05, * stands for p-value<0.1.

Table 16: Placebo Regression - All Women

	Nonwhite	HS	Age
	(1)	(2)	(3)
K	0.030***	0.157***	6.049***
	(0.007)	(0.008)	(0.147)
B	0.528	-0.413	1.628
	(0.415)	(0.328)	(4.666)
$K \times B$	-0.186	0.864	-0.826
	(0.142)	(0.455)	(2.730)
county	Yes	Yes	Yes
date	Yes	Yes	Yes
age	Yes	Yes	
educ	Yes		Yes
race		Yes	Yes
Estimator	OLS	OLS	OLS
N	909,430	909,430	909,430
R^2	0.161	0.167	0.288

Columns show results for (1) a binary variable indicating if the individual is nonwhite, (2) a binary variable indicating if the individual graduated from high school, (3) and age. Standard errors clustered at the state level. *** stands for p-value<0.01, ** stands for p-value<0.05, * stands for p-value<0.1.

Table 17: Auxiliary Moments

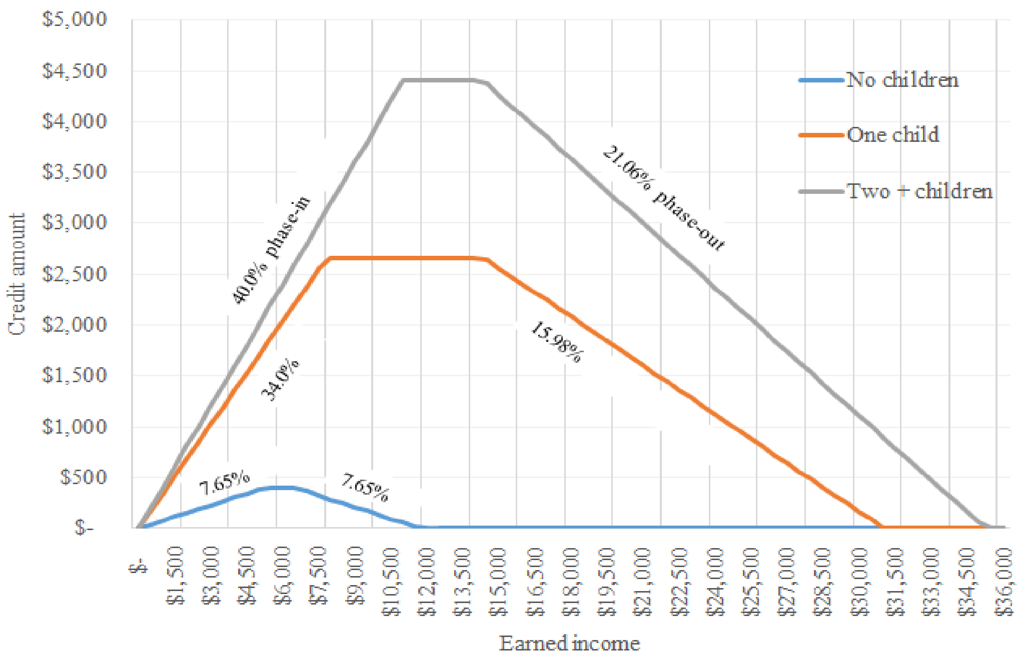
		Data		Model
		Moment	Standard Error of Moment	Moment
EU Transition Rate	<30 Years	0.090	0.005	0.093
Employment Rate	<30 Years	0.569	0.006	0.589
Share FT Employment	<30 Years	0.688	0.007	0.668
J2J Transition Rate	<30 Years	0.031	0.003	0.031
Share MJH	<30 Years	0.019	0.002	0.020
Mean lw	<30 Years	2.258	0.014	2.238
EU Transition Rate	31-40 Years	0.048	0.003	0.034
Employment Rate	31-40 Years	0.705	0.005	0.677
Share FT Employment	31-40 Years	0.794	0.006	0.831
J2J Transition Rate	31-40 Years	0.025	0.003	0.016
Share MJH	31-40 Years	0.035	0.002	0.035
Mean lw	31-40 Years	2.451	0.014	2.498
EU Transition Rate	>=41 Years	0.045	0.003	0.031
Employment Rate	>=41 Years	0.692	0.005	0.702
Share FT Employment	>=41 Years	0.820	0.005	0.800
J2J Transition Rate	>=41 Years	0.022	0.002	0.017
Share MJH	>=41 Years	0.046	0.002	0.048
Mean lw	>=41 Years	2.534	0.014	2.530
EU Transition Rate	One Child	0.060	0.003	0.051
Employment Rate	One Child	0.676	0.004	0.675
Share FT Employment	One Child	0.786	0.005	0.804
J2J Transition Rate	One Child	0.025	0.002	0.023
Share MJH	One Child	0.036	0.002	0.030
EU Transition Rate	Two Children	0.056	0.003	0.049
Employment Rate	Two Children	0.639	0.004	0.638
Share FT Employment	Two Children	0.765	0.005	0.736
J2J Transition Rate	Two Children	0.025	0.002	0.018
Share MJH	Two Children	0.032	0.002	0.039
Mean lw	PT Workers	2.190	0.018	2.245
Mean lw	FT Workers	2.493	0.009	2.475
25th pctile. Δ lw	All	0.244	0.014	0.114
50th pctile. Δ lw	All	0.492	0.017	0.798
75th pctile. Δ lw	All	0.750	0.014	0.869
Employment Regression	B*K Coefficient	0.517	0.151	0.508
MJH Regression	B*K Coefficient	0.225	0.063	0.189
J2J Regression	B*K Coefficient	0.096	0.040	0.086

B 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 5 shows the credit amount as a function of earned income and number of qualifying children, as of year 2005. The credit first increases linearly with earnings in the phase-in region, then plateaus over a given income range, and then decreases linearly in the phase-out region. In 2005, the phase-in credit rate was 34% for individuals with one child and 40% for individuals with two or more children; the corresponding phase-out rates were 15.98% and 21.06%. Families with resident children are bound to receive a significant credit. The maximum credit was $2,662 and $4,400 for taxpayers with one child, and two or more children, respectively. Individuals with no children only received a small credit, with a 7.65% phase-in rate and a maximum credit of $399. The credit clearly targets families with low to moderate income: the maximum income to receive the credit was $31,030 and $35,263 for taxpayers with one child, and two or more children, respectively.

Figure 5: 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.

C Hidden Markov Model: Estimation and Results

The Hidden Markov Model (HMM) consists of measurement parameters, $(\{\kappa_\tau\}_{\tau=1}^{N_c}, \sigma_m)$, the probability of an increase in awareness, π, and the prior probabilities of type, $\{\pi_{\tau,0}\}_{\tau=1}^{N_c}$. In the main body of the paper we labelled these parameters as Ω_1. In order to estimate Ω_1, we set $N_c = 4$, $Q = 10$, and apply the *Expectation-Maximization* algorithm:

1. Fixing a guess of the parameters, $\hat{\Omega}_1$.
2. For each county c, use $\hat{\Omega}_1$ to calculate posterior probabilities,
$$\mathbb{P}\left[\tau(c) = \tau, P_{ct} = q \middle| \hat{\Omega}_1,\ \{B_{ct}\}_{t=2000}^{2009}\right]$$
for each $\tau \in \{1, .., 4\}$, $q \in \{1/Q, ..., 1\}$.
3. Use the posterior probabilities to construct a likelihood, $L(\omega|\hat{\Omega}_1)$ and estimate:
$$\tilde{\Omega}_1 = \arg\max_{\omega} L(\omega|\hat{\Omega}_0)$$
4. Check the convergence criterion for $||\tilde{\Omega}_1 - \hat{\Omega}_1||$. If satisfied, terminate the algorithm with the estimate $\hat{\Omega}_1$. Otherwise, set $\hat{\Omega}_1 = \tilde{\Omega}_1$ and return to step (1).

We use the Forward-Back algorithm in order to calculate the posterior probabilities, following the *Baum-Welch* approach (see Baum and Petrie (1966), for example). Arcidiacono and Miller (2011) provide a useful discussion of the EM algorithm in an economic setting with endogenous choices.

In order to calculate standard errors, we draw, with replacement, 100 samples from the population of counties, and perform one iteration of the EM loop described above. We use this same sample of counties when calculating statistics for the indirect inference procedure, thereby allowing for the correct statistical dependence between first and second stage estimates.

Table 18: Parameter Estimates from the Hidden Markov Model

Parameter	Estimate
π	0.258
	[0.253;0.263]
σ_m	0.131
	[0.128;0.134]
κ_1	-4.1200
	[-4.121;-4.120]
κ_2	-3.634
	[-3.635;-3.633]
κ_3	-3.370
	[-3.371;-3.368]
κ_4	-2.770
	[-2.775;-2.766]
$\pi_{1,0}$	0.473
	[0.461;0.484]
$\pi_{2,0}$	0.246
	[0.238;0.254]
$\pi_{3,0}$	0.216
	[0.208;0.224]
$\pi_{4,0}$	0.066
	[0.058;0.074]

95% bootstrap confidence intervals in parentheses. π is the probability that each county moves up one point in the awareness grid. κ_τ is the intercept for counties of type τ in the measurement equation (6), σ_m is the standard deviation of the measurement shocks, ϵ_{ct}, and $\pi_{\tau,0}$ is the prior probability that a given county is of type τ.

D Welfare Formula from Marginal Tax Reform

Let $\mathbf{u}$ denote the vector of utilities in each state i. Let λ_{ij} be the (endogenous) rate at which a worker transitions from state i to state j, and construct the matrix Λ as:

$$\Lambda_{ij} = \begin{cases} \lambda_{ij} & \text{if } i \neq j \\ -\sum_{j \neq i} \lambda_{ij} & \text{if } i = j \end{cases}$$

Now, we can write the Bellman operator as:

$$rV = \mathbf{u} + \Lambda V$$

which has solution:

$$rV = r(rI_N - \Lambda)^{-1}\mathbf{u} = \Omega\mathbf{u}.$$

We first note that each row of Ω sums to 1. This follows from the observation that $\Lambda\mathbf{1}_N = \mathbf{0}_N$ by construction, and the application of simple matrix algebra. It will also help to note that if π is the current distribution of workers over states, we have:

$$d\pi = \Lambda'\pi$$

and so the stationary distribution π^* solves:

$$\Lambda'\pi^* = 0$$

Working with this condition gives

$$\begin{aligned} r^{-1}\Lambda'\pi^* &= 0 \\ \Leftrightarrow (I_N - r^{-1}\Lambda')\pi^* &= \pi^* \\ \Leftrightarrow \Omega'\pi^* &= \pi^* \end{aligned}$$

which will prove useful when applying a welfare function with equal pareto weights over individuals in the economy.

Now consider the vector $\tau \in \mathbb{R}$, representing the direction of a particular tax reform, and let γ dictate the overall intensity of the reform. The direct response here can be summarised by $\mathbf{u'}$, the vector of marginal utilities of consumption, while the behavioral effect is summarised by responses in Λ, which is a function of job acceptance decisions and exogenous contact rates. The marginal change in consumption is given by:

$$dc_i = \tau_i d\gamma$$

and so we get:

$$\left.\frac{drV_i}{d\gamma}\right|_{\gamma=0} = \sum_{j=1}^{N} \omega_{ij} u'_j \tau_j$$

for individuals in each state. As is typical, we can ignore the behavioral effect, $d\Lambda/d\gamma$, since job acceptance decisions only respond at points of indifference, and contact rates are otherwise exogenous. Finally, we exploit the fact that each row of Ω can be treated as a probability vector to write this as:

$$\left.\frac{drV_i}{d\gamma}\right|_{\gamma=0} = \mathbb{E}_{\omega,i}[u']\mathbb{E}_{\omega,i}[\tau] + \mathbb{C}_{\omega,j}(u', \tau).$$

That each ω_i can be treated as a probability vector is more than coincidental. The weights measure the relevance of future states for the purposes of an agent's welfare. Weights are higher for states that are more likely to be visited in the near future, and for states in which agents are likely to spend more time. This intuition can be assisted by two limit cases, and a low-dimensional example. First, observe that:

$$\lim_{r\to 0} \Omega = \pi^*, \qquad \lim_{r\to\infty} \Omega = I_N$$

In the first case, as agents become perfectly forward-looking, the weights trend to the ergodic distribution of states: the only thing that matters for welfare is the relative amount of time spent in each state. In the second case, as agents discount the future at greater and greater rates, only the current state becomes relevant for welfare. Intermediate cases balance these two extremes. For example, consider the case in which one job is offered, at rate λ, and destroyed at rate δ. We let states 1 and 2 refer to unemployment and employment. In this case we get weights:

$$\Omega = \begin{bmatrix} \frac{r+\delta}{r+\delta+\lambda} & \frac{\lambda}{r+\delta+\lambda} \\ \frac{\delta}{r+\lambda+\delta} & \frac{r+\lambda}{r+\lambda+\delta} \end{bmatrix}$$

These weights determine the dynamic incidence of a transfer, which depends not just on the current distribution of agents across states, but also on the extent to which agents in other states. These weights tell us that the willingness of employed individuals to pay for unemployment insurance, depends not just on the the risk of unemployment (δ), but the extent to which they discount the future (r), and the expected duration of that state (λ).

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