# Beating the Clock: Using Year-end Changes to Identify Intensive Margin Labor Supply Responses to Taxation

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**Abstract**

Identifying the effect of tax policy on the labor supply of individuals who would work regardless has been a longstanding empirical challenge. This paper proposes a new strategy for identifying workers' intensive-margin labor supply elasticity using within-calendar year variation in anticipated year-end tax rates. I modify the standard non-linear budget set approach to include uncertainty about future employment. With uncertainty, households must forecast their annual income in order to anticipate the average and marginal tax rates that apply to their earnings. I use survey and administrative data to measure how low-income households' earnings and employment vary within and across tax years, and evaluate whether households adjust labor supply in response to temporary changes in their net of tax wage. I conclude that household labor supply responds more to expected tax rates at the end of the year, when certainty about annual income is greatest. I use the excess sensitivity to tax incentives at the end of the year, relative to other periods, to estimate an intensive margin labor supply elasticity between .08 and .18. This response is identified largely from non-linearity in the Earned Income Tax Credit (EITC) schedule and implies a larger intensive margin response to this program than previous estimates.

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# 1 Introduction

Identifying the effect of taxes on the labor supply of people who would work regardless has been a longstanding empirical challenge. Despite the incredible policy relevance of this parameter, the micro literature lacks reliable estimates of the intensive margin response to tax incentives. Identification is challenging, in part, because it is difficult to isolate exogenous variation in marginal tax rates within nonlinear tax schedules, and in part because extensive margin responses to tax policies create sample selection that biases standard difference-in-difference analyses. Further, even credible average estimates mask important heterogeneous responses; we would expect larger responses to short-term variation in tax rates that can be avoided via intertemporal substitution than to longer-term variation, and it is not clear which are identified by many existing studies.

Concretely, understanding the impact of the Earned Income Tax Credit (EITC) on labor supply is an important topic for policy purposes. The EITC is the largest means-tested cash assistance program in the US and largely shapes the tax policy facing lower-income workers. There are many studies demonstrating the program's substantial effects on workers' extensive margin labor supply decision, but most analyses show zero effects on the intensive margin. This result is not wholly convincing, however, given the large changes to the composition of the workforce that reforms to the EITC induce (Nichols and Rothstein, 2015).

A possible explanation for the lack of a response, and an important unresolved issue in the labor supply literature, relates to workers' information structure. Labor supply models of non-linear budget sets (Hausman, 1982) estimate individuals' responses to their estimated tax rates, but it is not clear that the workers are aware of the rates that they face. This is a particular concern with nonlinear, annual tax schedules: The marginal tax rate on an individual's labor supply one day depends on total earnings throughout the year, and for many periods in a year, those earnings have not yet been realized. It seems likely that many low-wage workers, whose earnings are disproportionately volatile and whose income tax schedule is highly non-linear, have trouble forecasting their annual income and thus their marginal tax rate.

In this paper, I propose a new strategy for identifying short-term labor supply responses that exploits this uncertainty. The strategy is motivated by the fact that some workers face uncertainty about their annual earnings, and that uncertainty is gradually resolved as the tax year progresses. At the beginning of the year, workers' forecasts of their annual earnings and their marginal tax rates are imprecise, but because they gain more information with each work day, they can make more accurate estimates of the tax rate that will ultimate apply to those earnings. As a result, we might expect workers' labor supply to depend more strongly on their expected annual tax rates in the fourth quarter, when one's employment history is nearly realized, than in the first.

I exploit this idea to obtain a new measure of the intensive margin Frisch elasticity. I use the difference in awareness of true tax incentives between the beginning and end of the tax year to distinguish workers' independent response to tax policy from standard serial correlation in earnings. I interpret the excess sensitivity of earnings to likely tax incentives in the fourth quarter, relative to other calendar quarters, to reflect workers' intentional reallocation between labor and leisure in response to those tax incentives.

I evaluate whether workers make these year-end adjustments, and I measure the size of this response, using two data sources: the Survey of Income and Program Participation (SIPP) and administrative earnings records for lower-income Californians enrolled in the Supplemental Nutrition Assistance Program (SNAP). Both datasets contain within-year earnings and information needed to identify households' tax rates. I construct likely tax units from SIPP households and SNAP cases. I measure each workers' total earnings through multiple within and cross-year periods. I identify predicted marginal and average tax rates for each tax unit in each of those periods using National Bureau of Economic Research's TAXSIM program. To measure households' labor supply response to their expected tax rate, I relate earnings in each period to the average tax rate that would apply on that period's predicted earnings. I separately identify this response in each calendar quarter, and test whether this relationship appears strongest in the final quarter of the tax year.

My approach assumes other differences in labor supply and demand across the tax year do not vary with workers' earnings levels. In other words, workers do not exhibit greater response to tax incentives at year's end except for this lessened uncertainty, and employers do not especially increase demand for workers facing the most negative tax rates. That work might increase (or decrease) on average in the final quarter due to national holidays, for example, does not threaten my identification, unless workers with the most negative tax rate always increase labor supply the most during the holiday season. To account for any lingering omitted variable bias concerns, I measure employment responses among the same workers and households over multiple consecutive years. This household fixed-effects strategy accounts for individuals' constant unobserved preferences, characteristics, and seasonal employment patterns that could bias my findings.

I conclude that household labor supply is indeed more sensitive to expected tax incentives at the end of the tax year. For a 10 percent increase in their predicted net of tax wage rate, households increase earnings in the fourth quarter by 1 to 2 percent on average. This response is largely driven by households facing the most negative tax rate at year's end. When the same household is projected to have modest annual earnings, such that they would expect to be on the phase-in segment of the EITC schedule, it tends to increase their earnings in the following quarter. This response is significantly larger at the end of the tax year, suggesting that adjustment is not due to mean reversion. However, I find no evidence that households facing steeply positive marginal tax rates – those with earnings on the phase-out part of the EITC – reduce their labor supply.

My primary empirical strategy assumes that labor supply choices early in the year are not made based on worker's expectation of their end-of-year tax rate. While uncertainty about annual earnings makes this likely to be close to accurate, it may not hold exactly. To assess the importance of this assumption, I estimate an alternative model in which I test whether households adjust earnings earlier in the year based on their expectation of year-end tax incentives. My main result still holds, however; earnings responses are more sensitive to forecasted tax incentives nearer the end of the tax year. This supports the interpretation of my main estimates, in that they reflect labor supply elasticity rather than bias.

My approach boasts several advantages over other strategies for measuring labor supply elasticity. First, I overcome classic econometric issues that plague most other empirical approaches. (See Keane, 2011, for a summary). I address the "taste for work" bias problem by controlling for to-date earnings and measuring adjustments with the same household over multiple years. I address the issue of simultaneity by instrumenting for workers' current net wage using their predicted year-end after-tax income. This instrument also addresses concerns about mismeasurement of hours and earnings. Second, my approach overcomes the selection and composition issues that bias difference-in-difference evaluations (Nichols and Rothstein, 2015). Third, I address external validity concerns inherent to investigations of unique tax reforms by studying a common and regular setting faced by many different workers in different places over many different years. Fourth, I do not rely on a structural model with strong parametric assumptions.

To make this approach more tractable, I propose a finite, multi-period model of labor supply in which a representative agent, who aims to maximize utility over consumption and leisure, decides at the start of each period how much to work. The agent makes this decision given her to-date earnings, uncertainty about being employed in this and future periods, a non-linear tax schedule, and parameters governing preferences and probability of employment. I solve the agent's choices via dynamic programming. I map out all possible sequences of employment states, earnings and hours choices, and tax liabilities across twelve periods. Using backward induction, I identify the agent's labor supply choice in the last period given possible earnings to date. In the first period, the agent will choose a preferred bundle of work and leisure based on their expectation of future employment. As she realizes her employment history, the agent gains more certainty about her total annual income and expected tax rate. In response, the agent's preference between labor and leisure becomes more sensitive to previous earnings. As the final period approaches, the agent enjoys the greatest clarity about, and is most responsive to, her expected tax rate. I conclude that households facing a less positive tax rate tend to increase labor supply in the final period in order to maximize post-tax income, and workers facing a more positive tax rate will work less. These adjustments result in greater bunching in proposed annual income as the tax year progresses. Uncertainty, plus reasonable compensated elasticity, yield earnings densities that resemble those observed empirically.

This paper makes a number of important contributions to several literatures in labor and public economics.

First, this paper contributes to an extensive literature studying both the extensive and intensive margin Frisch elasticity (Altonji, 1986; Angrist, 1991; Blundell et al., 2016; Card and Hyslop, 2005; Keane, 2011; Kimball and Shapiro, 2008; Laitner and Silverman, 2005; MaCurdy, 1981; Manoli and Weber, 2016; Pencavel, 1986; Pistaferri, 2003) and how transitory changes in wages and tax policy affect labor supply choices (Camerer et al., 1997; Crawford and Meng, 2011; Farber, 2008; Fehr and Goette, 2007; Martinez et al., ming; Powell, 2015; Stafford, 2015). Much of this work focuses on the relevance of those shocks in life-cycle models (Heckman and MaCurdy, 1980; Keane and Rogerson, 2012; Keane, 2011). I study how income and employment shocks affect workers short-run labor supply behavior. My estimate of the Frisch elasticity is similar to those in the micro-literature summarized by Reichling and Whalen (2012).

Second, this paper contributes to another extensive literature measuring labor supply and taxable income elasticity using non-linear budget sets (e.g., Blundell et al., 2009, 2000; Blundell and MaCurdy, 1999; Burtless and Hausman, 1978; Hausman, 1985; Keane and Moffitt, 1998; MaCurdy et al., 1990; Moffitt, 1990), and a related literature investigating using "bunching" at kink points in tax schedules to measure the same elasticities (Blomquist and Newey, 2017; Kleven and Waseem, 2013; Saez, 2010). The nonlinear budget set is the starting point for my model; I expand it by permitting agents to adjust their labor supply choice over time. I provide important context to Saez's (2010) well-known result, arguing that individuals try to move toward kink points but are precluded from perfectly bunching by numerous frictions.

Third, this paper adds to a newer literature measuring the size and relevance of those frictions. Chetty et al. (2011) and Gelber et al. (2020) both measure the importance of adjustment frictions in mitigating labor supply responses to tax and transfer policy. Liebman and Zeckhauser (2004) and Rees-Jones and Taubinsky (2019) study how workers respond to marginal versus average tax rates. Chetty et al. (2013), Feldman et al. (2016), and Miller et al. (2015) study how complexity and salience of tax policies matter to workers' labor supply choices. I contribute to this literature by measuring the relevance of uncertainty about future employment – an oft-cited but under-studied type of an optimization friction – to labor supply choices. I also document that workers are appear more responsive to the average tax rate, as opposed to the marginal tax rate, that will likely apply to their out-period earnings.

Fourth, this paper adds to the literature investigating labor supply effects of the EITC. Much of the nonlinearity in tax incentives that I study is due to the EITC's structure, especially for households with children. Accordingly, this paper can largely be understood as a study of households' response to this program. A large literature concludes that the EITC draws individuals into the workforce (Eissa and Liebman, 1996; Gelber and Mitchell, 2011; Grogger, 2003; Hotz and Scholz, 2006; Meyer and Rosenbaum, 2001), but there is limited to no evidence of an intensive-margin response, despite clear theoretical predictions that it should have such an effect (Eissa and Hoynes, 2006; Hotz, 2003; Nichols and Rothstein, 2015; Saez, 2010).

There are two notable exceptions to this near consensus finding. Using apparent variation in local knowledge about the EITC schedule from tax return data, Chetty et al. (2013) identify how labor supply changes in response to the birth of a child across areas with more or less awareness of the EITC's incentives. They estimate an average intensive margin earnings elasticity of .14 in the phase-out region and .31 in the phase in region. These authors' identification focuses on differences in labor supply of a parents in the year in which their first child is born, which is both a unique population and unique setting – raising concerns about their findings' external validity. The second paper, Chetty and Saez (2013), also study how awareness of the EITC's incentives affect labor supply via an experiment where some taxpayers were informed about the program's structure. They find a small (3 percent) increase in average earnings among treated subjects, implying a labor supply elasticity of .075 (Nichols and Rothstein, 2015). Like these studies, I use differences in workers' awareness of their tax incentives to identify a labor supply response to the EITC. I also find a non-zero intensive margin response to the EITC, similar to these studies but in contrast to the rest of the literature. My preferred estimates are also quite similar to these authors' results. Unlike Chetty et al. (2013), I find that this effect is driven entirely by households with the lowest earnings, those facing a negative average and marginal tax crated created by EITC's phase-in. I find no evidence in labor supply reduction by households predicted to be in the phase-out part of the EITC schedule.

Fifth, this paper extends a small literature that documents how workers' labor supply can vary within the tax year. Yang (2018) and Powell (2020) both study labor supply effects of receiving a lump sum cash payment (i.e., EITC disbursement and 2008 stimulus payments). Each of these authors document an important extensive margin response due to the income effect. In contrast, this paper studies the relevance of the substitution effect on households' within year labor supply behavior. More similar to this study, Wilson (2020) uses the panel-nature of the CPS to document how EITC expansions decrease workforce exits and increase overall months worked among single mothers. Looney and Singhal (2006) study how losing a dependent exemption from aging children affects households' labor supply behavior in the short-term.

Finally, this paper makes an important contribution to policy-relevant discussions about potential reforms to tax-based means-tested programs like the EITC. Policymakers continually express interest in reforming the EITC so that it subsidizes households' earnings throughout the tax year instead of one lump sum (Jones, 2010; Maag, 2019). If household earnings and tax liabilities fluctuate enough, this raises important issues with the viability of such reforms. This study provides evidence about how households exhibit large changes in expected EITC eligibility across and within years. I also demonstrate for which households these predictions are likely to be most wrong.

The paper proceeds as follows. In Section 2, I describe my model. In Section 3, I describe the SIPP and the California administrative data, how I convert households in these data to tax units, and how I estimate households' tax rates using TAXSIM. In Section 4, I use these data to show the extent of non-linearity in the income tax schedule facing low-income households as well as variability in household income and tax rates over the year. In Section 5, I describe my empirical analysis. In Section 6, I summarize my results. In Section 7, I conclude.

## 2 Model

Consider the quasi-linear and isoelastic labor supply utility model proposed by Saez (2010). A worker with ability $n$ aims to maximize utility over consumption $c$ subject to a cost from working, which she only pays if she's employed. $z$ denotes workers' pre-tax earnings, which are the product of the worker's wage $w$ and labor supply choice $h$. $e$ indexes the worker's compensated elasticity. Consumption $c$ equals net of tax earnings: $(1 - \tau(z))z$. The worker faces a single-kinked tax schedule. Earnings below a threshold $\bar{z}$ are taxed at a rate of $\tau_0$, and earnings above the threshold are taxed at a rate of $\tau_1$, where $\tau_1 > \tau_0$. [1]

$$u(c, z) = c - \frac{n}{1 + \frac{1}{e}} \left(\frac{z}{n}\right)^{1+\frac{1}{e}}$$

Saez's (2010) model assumes each worker makes a single labor supply choice $l^*$. I modify the model to incorporate sequential choices of labor supply and uncertainty about future earnings. Suppose a worker chooses a labor supply level $h$ in each of $D$ periods that comprise the tax year, and in each period, the worker is actually employed at $h$ with probability $p$. The worker earns pre-tax income $z_d = wh_d$ in period $d$ if employed and $0$ if not. She only pays the cost of work if employed. The worker still aims to maximize utility subject to the same disutility from working. Her net of tax wage rate depends on total earnings across all $D$ periods. The optimal labor supply $h^*$ in any period $d$ depends on to-date earnings, the worker's forecast of future employment, and how she will adjust $h$ in future periods in response to her realized employment.

Given values for parameters $p, \tau_0, \tau_1, n$, and $e$, we can identify the agent's labor supply choice $h$ for any level of $z_{D-1}$ via dynamic programming. We solve the agent's labor supply decision recursively, beginning in period $D$ and ending with period 1.

$$V_d(h_d) = \max u(c, l|\Sigma_{t=1}^{d-1} z_t) + V_{d+1}(l_{d+1})$$

The agent faces the following maximization problem in the final period.

$$\begin{aligned} u(c, h|z_{D-1}) =& p\left(c - \frac{n}{1 + \frac{1}{e}} \left(\frac{h}{n}\right)^{1+\frac{1}{e}}\right), \\ & \text{where } c = \begin{cases} (1-\tau_0)(wh + z_{D-1}), & \text{if } (wh + z_{D-1}) \leq z^* \\ (1-\tau_0)z^* + (1-\tau_1)\big((wh + z_{D-1}) - z^*\big), & \text{if } (wh + z_{D-1}) > z^* \end{cases} \end{aligned}$$

Given to-date earnings $z_{D-1}$, the agent chooses optimal $h^*$. Taking an expectation over

[1] Saez (2010) shows that, with a continuous ability parameter $n$, the size of the mass in the earnings distribution clustered around $z^*$ is determined by the compensated elasticity $e$. Saez (1999) shows that if workers actually earn $z + \epsilon$, this bunching would appears more as a dispersed mass as opposed to an atom, but the model still taxpayers mass at the kink $\bar{z}$.

likelihood of being employed, the agent knows whether her total earnings $wh + z_{D-1}$ will exceed $z^*$ or not. Her calculation of $h^*$ is the same as in the single period model.

Given the agent's choice of $h$ for all possible values of $z_{D-1}$, we move backward to the previous period. For each value of $z_{D-2}$, the agent chooses $h^*$ for all values of $z$ to maximize the same utility function as above, knowing the value of $h$ she will choose in the next period given her choice in this one. Given her choice of $h^*$, we can move backward to the previous period, and so on.

I solve this model for a particular set of values $D, p, \tau_0, \tau_1, z^*$, and $e$. I present results from a model in which I use $D = 12$, $p = .8$, $\tau_0 = 0$, $\tau_1 = .3$, and $e = .5$, but results are qualitatively similar for alternative values for each parameter. For each period, I construct a grid of discrete levels of possible to-date earnings and hours choices, $z \times l$, where $z = [0, d \times wh_{\text{max}}]$ and $h = [0, w(1-\tau_0)^{\frac{1}{e}}]$.[2] I solve the agent's maximization problem, specified above, for all possible discrete levels of $z$ in each period.

Figure 3 presents the labor supply choices in each period for a agent with $n = 1$. For any average hours worked per period to date, the agent has a unique labor supply choice $h$ in each period that she expects will maximize her expected utility. In the second period, the worker is fairly insensitive to hours worked in the first. As time progresses, the worker becomes more sensitive to average hours worked to date. If average hours worked is low, meaning the worker experienced a number of unemployed periods, she proposes to work her maximum number of hours in the next period. If average hours worked is high, the worker scales back her hours choice and chooses to work her minimum. In the final period, when future uncertainty is minimized, the worker simply chooses to work $h_{\text{max}}$ if to-date earnings are sufficiently low, or the lowest level of $h$ at which consumption still exceeds the cost of work.

Panel A in Figure 4 presents the same results but for three agents with different levels of ability $n$. This means these agents incur different costs from work and will have different optimal labor supply choices. Though levels and sensitivities vary, the overall pattern is the same. Workers choose $h_{d=2}$ given an expectation of future employment, but labor supply choices change in each period as that uncertainty is resolved. All three agents choose to work the maximum number of hours if average hours to date are low, meaning they have a low chance of facing tax rate $\tau_1$.

Panel B in Figure 4 presents results for three agents with the same ability $n$ but three different elasticities $e$: : .1, .25 and .4. Changes in $e$ reflect workers' sensitivity to the change in the cost of work. Though levels and sensitivities vary, the overall pattern is the same. Workers choose $h_{d=2}$ which reflects an expectation of future employment, but labor supply choices change in each period as that uncertainty is resolved. All three agents choose to work the maximum number of hours if average hours to date are low, meaning they have a low chance of facing tax rate $\tau_1$.

[2]Specifically, I use 200 possible hours choices and 500 earnings possibilities. Using a coarser or richer grid would not affect my main results.

Next, I solve the model for 500 levels of $n$. I draw random levels of $n$ from $\sim \mathcal{N}(.9, .01^2)$. For each $n$, I solve the full dynamic programming model, saving all possible earnings and choices in each period. I then select a single earnings sequence for each agent. I select a sequence by, first, identify each agent's $h^*_{d=1}$. The agent works that amount with probability $p = .8$, and she works zero hours with $p = .2$. Given the hours choice in the first period, I recover the agent's proposed hours choice in each subsequent period, and in each, I randomize whether they are actually employed at that hours choice with $p = .8$. I then identify how the worker responds in the subsequent period given her new average hours worked to date, and so on. This simulation yields one employment history for all 500 levels of $n$. I repeat this same process for the three different levels of $e$ used above.

Figure 5 presents the kernel densities of proposed annual earnings for all agents as of the end of period 4, 8 and 12. There are three main takeaways from this simulation. The first is that agents exhibit greater bunching in proposed annual earnings at the end of the year than earlier in the year. As of period 4, the distribution exhibits limited mass at the kink point,[3] but as time progresses and labor supply decisions move toward each agent's extreme, bunching increases. The second takeaway is that the amount of bunching is affected by workers' elasticity. Workers with higher elasticity are more sensitive to tax policy, and exhibit greater bunching, as predicted. The third takeaway is that, with a low elasticity, bunching is not conspicuous enough to be identified from standard bunching estimator. However, the earnings distribution at year's end[4] is distinguishable from the distribution of predicted annual earnings as of period 4, and the difference between these distributions is due to agent's sensitivity to tax policy.

## 3 Data

### 3.1 SIPP

I use the 1996, 2001, 2004 and 2008 panels of the Survey of Income and Program Participation (SIPP).[5] The SIPP is a nationally representative sample of approximately 35,000 households administered by the Census Bureau over the course of three to four years. Respondents are interviewed about their employment, hours worked, wages, earned and unearned income, household composition, and participation in government programs, among much else, every four months. Most important for my purposes, the SIPP asks respondents to report employ-

[3]The distribution is bi-modal because some workers will proposed to work more early in the year, anticipating that they might become unemployed at some point, but in fact are employed in each period. This adjustment captures a negative intensive margin response to $\tau_1$. An alternative set of parameter values could yield a mass of workers with low proposed earnings who increase labor supply as the year progresses.

[4]One can think of this distribution as the earnings researchers observe in annual tax data.

[5]I do not use the most recent SIPP panel fielded between 2013 and 2017. SIPP respondents are now asked to recall employment, earnings, and program participation for each month in the calendar year. I find that this reform tends to worsen cross-calendar year seam bias, which poses a unique threat to my approach. I find that employment rates exhibit a distinct discontinuity within households between December and January that I do not observe in other panels.

ment and earnings information at the time of the survey and recall this information for each of the three previous months. The SIPP is the only survey that captures individual and household earnings at multiple continuous periods across multiple calendar years.

I identify likely tax units from SIPP survey units. Changes to the composition of SIPP households introduces challenges for credibly identifying workers' true tax liabilities, so I limit my analysis to households that contain only one family, following Yang (2018). I further restrict to households for whom I have complete information about earnings, employment and household configuration throughout each calendar year for all household members. This restriction ensures that my estimates of tax liability are not confounded by either changes in household composition or missing earnings information. I also restrict to households that include at least one working-age member between the ages of 25 and 55, and I restrict to households where only the household head and spouse, as opposed to siblings or adult children, have earnings, because I cannot distinguish whether these households reflect a single or multiple tax units.

Finally, I restrict to households who have non-zero earnings in every calendar quarter, and whose total earnings in any set of three consecutive quarters is between \$2,000 and \$75,000. The purpose of these restrictions is to focus only on the intensive margin response and limit attention to households who have are more likely to face some uncertainty in their tax rates.

My final sample includes earnings information for approximately 12,000 unique households and 18,000 unique tax units (ie, households by tax year). Table 1 summarizes average values for key demographic characteristics in my sample, and how my restrictions affect the composition of my sample.

For each tax unit, I identify each head and spouses' total earned income in each month from both wages and self-employment. I sum both sources of earnings within each wave and quarter for each tax year. I also identify each households' unearned income each month (ie, Social Security, other pension and unemployment insurance benefits).

SIPP households also complete various supplemental interviews in each panel. Two of these topical modules ask respondents about variables particular to tax filing, including: property tax bill, amount of itemized deductions, retirement account contributions and deductions, capital gains and losses, and child and dependent care expenses. When available, I associate each adult in each tax unit with tax-relevant variables from these topical modules.

### 3.2 California Administrative Data

I start with program rosters for California's instantiation of SNAP, known as CalFresh, between 2014 and 2017. These records capture every recipients' per month enrollment in the program, the cases in which they were enrolled, and their demographic characteristics. In 2017, I observe approximately 5.6 million unique individuals across 2.9 million unique SNAP cases. Of these 5.6 million individuals, 2.5 million were younger than 18. Total caseloads are fairly constant over the four years in my sample.

I associate each adult enrolled in SNAP with their quarterly employer-reported earnings records. These records are collected by the CA Employment Development Department (EDD), which administers the state's unemployment insurance program. I observe the earnings of each individual for six quarters prior to their enrollment in SNAP, every quarter in which they're enrolled, and 18 months after their last month enrolled. This means that even if an adult is only enrolled for a handful of months in 2016, I still observe their earnings for most, if not all of, 2015 and 2017.

I then match each individual in the SNAP program rosters to the universe of California state tax returns between 2015 and 2017. For each return, I observe basic information about the composition of the tax unit, as well as all variables on the primary state tax form (Form 540). For e-filed returns, I also observe all variables on the Form 1040. I also observe select variables from individuals' information returns, including total wages reported on the W2. Between 33 and 34 million individuals appear on a state tax return in each tax year.

Of the 5.6 million individuals enrolled in SNAP in 2017, about 3.7 million appeared across 1.9 million unique state returns in tax year 2017. Roughly 38 percent of those 3.7 million were a head or a spouse on a return, and the remainder were dependents. These counts and fractions are fairly stable over the three years in my sample. Of the 1.4 million individuals who enrolled in SNAP and appear on a return as a head or spouse, 77 percent have positive EDD wages.

For my primary sample, I implement similar restrictions to those I applied to my SIPP sample, again, in order to focus attention on working-age households firmly attached to the labor force and for whom I can confidently estimate likely tax rates. I limit to households with an adult between the ages of 25 and 55, who have non-zero earnings in all quarters in each tax year, and whose earnings in any consecutive sequence of three quarters is between $2,000 and $75,000. I further restrict to California tax units in which all members were enrolled in SNAP for at least one month in the respective tax year and whose reported AGI matches their total quarterly earnings. I limit my analysis to these households in order to ensure that I can infer changes in true tax incentives based on changes in quarterly earnings. If tax units contained other adults with earnings or earnings from non-UI covered employment, then I could not rely only on quarterly earnings to predict future tax incentives. Table 2 summarizes how these restrictions affect the characteristics of my sample.

### 3.3 TAXSIM

I use NBER's TAXSIM program to identify households' average and marginal tax rates (Feenberg and Coutts, 1993). TAXSIM allows users to input key tax-related information for a given household, and returns income tax calculations using federal and state income tax policies for any year between 1960 and 2023. I input filing status, state, number of dependents, ages, earned and under income, and a variety of possible deductions. The program returns federal and state income tax liabilities and marginal tax rates (inclusive and exclusive of FICA taxes), federal and state EITC amounts, and more for all households. I use TAXSIM to identify how households' likely tax rates and liabilities change over the course of the tax year by summing household earnings over various periods and inputting these sums into TAXSIM. For example, if I want to identify the likely tax rate on a household's fourth quarter earnings, I sum that household's earnings through the first three quarters of a tax year, and input this sum, as opposed to a households' true annual income.

# 4 Motivation

## 4.1 Non-linear Tax Policy

I use output from TAXSIM to document cross-sectional variation in average and marginal tax rates for households in the SIPP and SNAP samples.

Figure 6 illustrates how average and marginal tax rates vary by household income in 1997 versus 2012 for married SIPP households with 0, 1, 2 or 3+ dependents. I group households into bins of $2,500, and within each bin, I calculate the average marginal and average income tax rates (combining federal and state income taxes as well as payroll taxes) that all households within that bin face on their annual earnings.

Households with children and modest earnings tend to face a steeply negative marginal and average tax rate on annual income. In 2012, the average household with children and annual earnings below $10,000 faced a marginal tax rate between negative 30 and 50 percent. Income taxes boosted these households' net income by 30 to 40 percent. When pre-tax household income eclipses about $45,000, the average tax rate settles around 30 percent, regardless of the household's number of children.

In Figure 7, I plot the marginal and average tax rate by number of dependents and annual income for single and married SNAP households in California in 2017. The patterns are roughly the same as in the SIPP sample. For households with children and incomes below roughly $10,000, marginal and average tax rates are steeply negative. Thanks to California's supplement to the federal EITC, they are even lower than the national averages. Households with children and income in the phase-in portion of the EITC face both a marginal and average tax rate between negative 50 and 75 percent.

Both figures make clear how important the EITC is for eligible households: negative marginal tax rates align with the phase-in part of the EITC schedule, and the highest marginal tax rates align with the phase-out range. When household income exceeds the maximum eligible income for the EITC, average and marginal tax rates appear to converge and hold steady at around 25 to 30 percent, regardless of household type. Figure 6 illustrates the impact of reforms to the EITC, which increased the maximum credit. Households with dependents and incomes below about $10,000 benefited from program expansions in 2001 and 2009, as well as the introduction of numerous state supplements.

The key takeaway, which is clear in both figures, is that similar households within a fairly narrow income range can face starkly different tax incentives as a function of their to-date earnings. As earnings rise from around $15,000 to $30,000, households quickly face steep positive marginal tax rates and positive tax liability.

These different tax rates will only impact labor supply if households appreciate that tax policy is non-linear. surveys and interviews of low-income workers suggest widespread awareness that tax filing is associated with receiving a refund (Edin et al., 2014; Halpern-Meekin et al., 2015; Smeeding et al., 2000), but only about half can recognize the EITC by name, (Bhargava and Manoli, 2015) and a minority are able to identify the mechanisms as to why they are receiving a refund or the program's benefit structure (Chetty et al., 2013; Smeeding et al., 2000). Still, surveys and ethnographic evidence documents an appreciation on the part of surveyed taxpayers that income tax policy boosts income for lower-income households (Halpern-Meekin et al., 2015). As long as households grasp that income tax policy has a means-tested structure – that it boosts income for those with the lowest earnings, but those benefits are reduced when earnings eclipse some level – then they grasp that earnings levels imply different tax incentives. This is all one needs to assume for income volatility to translate into tax uncertainty.

### 4.2 Income variation

Next, I illustrate how pre- and post-tax income varies significantly across the tax year for a substantial share of households. In the SIPP, I identify household income through each month of the calendar year, and in the California administrative data, through every quarter. Using this observed income, I project forward what household income might be for the entire year as of the end of each period. Using these income projections, I also identify each household's predicted year-end average tax rate through each period. I then calculate the differences between predicted and actual year-end income, as well as predicted versus actual year-end average tax rate. Finally, I show how this income volatility translates to fairly wide swings in expected tax rates across the tax year.

In Table 3, I report the share of SNAP and SIPP households for whom the absolute difference between their predicted annual income, predicted average and marginal income tax rates, and predicted total EITC amounts as of the end of each calendar quarter are more than particular units away from their year-end values. For one-third of households, predicted annual income as of the end of the first quarter is more than $5,000 from their actual annual income. By the end of September, however, this share falls to just 5 percent. Only three percent of households have a total EITC amount that is more than $1,000 different than their predicted EITC value as of the end of the third quarter. Table 2 also reports the average standard deviation for each variable within each tax year across all SNAP households. Figure 3 plots the distribution of standard deviations in predicted earnings within tax years across all SNAP households.

Table 4 also reports similar shares but compares differences between, as opposed to within, tax years. Cross-year variation is more significant than within-year variation, which reflects both how volatile earnings can be over longer time periods and how households gain clarity about likely earnings within tax years. The various panels in Figure 8 plot the distributions of these differences. The red dotted lines indicate the median of the absolute value of all the differences. In other words, half of all SNAP households experience a year-over-year change of at least $4,500 in wage earnings. This corresponds to half of households facing an average income tax rate which is more than seven percentage points different than what they faced the year before.

This variation does not necessarily imply unexpected volatility for all workers. Workers might be able to anticipate future spikes and dips in work hours and wages, which the researcher cannot observe. Workers might also choose to substitute when and how much they work in response to changes in the person opportunity cost of work, unrelated to tax incentives. Still, it is reasonable to expect that, especially for lower-income households, these variations do reflect volatility. Unemployment spells can be unanticipated, both in their occurrence and their length, which is why we have a large social program to insure against those risks. Firms also exert significant control over many workers' schedules, which translates into volatile hours worked and total earnings (Gerstel and Clawson, 2018; Golden, 2015; Maag et al., 2017; Schneider and Harknett, 2019). Even if wages are stable, year-end wage bonuses or unexpected dividends can also affect annual income and tax liability.

I cannot distinguish which of the households I observe in the SIPP or SNAP data are those whose change in earnings over time represents unanticipated volatility or intentional reallocations between labor and leisure. I rely on others' work demonstrating that volatility is common enough that a significant share of workers in both samples experience these idiosyncratic wage shocks, which creates an opportunity for workers to respond to them.

Figure 9 provides suggestive evidence that households do shift in the direction of maximizing their after-tax income. I plot the distribution of predicted annual earnings among SNAP households with two dependents in 2017 as of the end of quarter 1 and quarter 3, as well as their actual earnings. The distributions look fairly similar, reflecting that average distribution of quarterly earnings in the SNAP sample is fairly constant over time. Note, however, that a greater mass of SNAP households are predicted to have very modest earnings at the beginning of the year than later in the year. This mass appears to shift towards the center of the distribution, where households would maximize their total EITC receipt, by the end of the year. This shift mirrors the predictions from the model introduced in the previous section. It is suggestive of an increase in labor supply over the course of the tax year on the part of households facing a tax incentive to work more. Further, a greater mass of taxpayers appears to be near the second kink point of the EITC schedule as of the end of Q3, but that mass decreases in the following quarter. There is limited if any evidence of any shift on the part of households with earnings predicted to be in the phase-out portion of the EITC, however.

Figure 10 provides additional evidence that the change in the distribution in annual earnings reflects a shift along the EITC schedule. For all SNAP households, I identify their predicted state and federal EITC amounts as of the end of the third quarter, assuming that fourth quarter earnings equal the average of the first three. I subtract this amount from the households' actual EITC amount, and plot this difference over predicted annual income as of the end of the third quarter. Households whose predicted earnings would place them on the phase-in part of the EITC schedule exhibit the greatest difference between their actual and predicted EITC amount. These households appear to increase earnings at year's end in order to maximize their EITC amount.

Of course, the shifts identified in Figure 9 and Figure 10 may be due in part to mean reversion: households with low past earnings bounce back to a more normal earnings level over time. They might also reflect households with very low past earnings increasing their labor supply in order to achieve a basic subsistence of level of earned income. They might also simply be noise. I distinguish these explanations from a strategic response to tax incentives in my empirical analysis, which I detail in the following section.

# 5 Empirical Framework

Consider the simple cross-sectional estimation of the elasticity of labor supply with respect to net of tax wages:

$$\underbrace{l_i}_{\substack{\text{labor}\\\text{supply}}} = \alpha + \underbrace{\beta w_i}_{\substack{\text{net of tax}\\\text{wage rate}}} + \underbrace{\gamma y_i}_{\substack{\text{non-labor}\\\text{income}}} + \underbrace{X_i'\delta}_{\substack{\text{demographic}\\\text{controls}}} + \varepsilon_i \tag{1}$$

$\beta$ captures uncompensated wage effects on labor supply $l$, and $\gamma$ captures income effects. Estimates of $\beta$ using cross-sectional variation in $w$ are biased due to omitted variable and simultaneity: "taste for work" is correlated with $w$, and changes in $l$ affect $w$ via the tax rate the agent faces. To overcome both concerns, recent work estimates $\beta$ by measuring employment responses to tax reforms that affect similar workers differently where changes in $w$ are plausibly exogenous. However, these analyses regularly use repeated cross-sectional surveys to identify how employment rates change between treated and untreated workers. If tax reforms affect the composition of these groups of workers (and estimates of non-zero extensive margin effect imply they do), then we cannot rely on these settings to identify intensive margin effects. That reforms might also affect the equilibrium wage raises additional identification concerns (Rothstein, 2010).

I proposed to identify $\beta$ by measuring how earnings change in response to changes in expected tax rates faced by similar workers within the same tax year and the same worker across subsequent tax years.

I estimate this response via two empirical models. Both approaches borrow from the basic

OLS cross-sectional set-up in that I regress a measure labor supply in a given period, $y$, on an observation's expected net of tax wage rate for that period, $\omega$, along with a variety of controls. The models differ in how I define and instrument for $\omega$ and test for varied earnings responses across the tax year. In the first model, I use a "rolling window" approach in which I identify each households' predicted net of tax earnings rate in the following quarter, based on earnings from the previous three quarters. In other words, I create simulated tax years for each household, comprised of all possible sequences of four consecutive quarters. I distinguish response to tax policy from standard serial correlation in earnings across time by comparing the response in the simulated tax year that coincides with the actual tax year to those that end in the first, second or third calendar quarter.

In the second model, I instrument for households' expected net of tax wages rates using similar household's actual year-end tax incentives, and test whether households regularly adjust labor supply in response to their predicted year-end tax incentives. As mentioned in the introduction, this model is meant to account for the fact that households could anticipate their true year-end tax incentives from information other than past earnings and adjust labor supply in the near-term accordingly.

Both models address the econometric issues that plague standard estimations of Equation 1. I address simultaneity by instrumenting for $\omega$ using predicted net of tax wage rates. I also account for omitted variable bias by estimating responses within the same household over consecutive years. I also control for to-date earnings, which also helps to mitigate "taste for work" bias and dynamic earnings patterns.

Below, I describe each model. In the following section, I summarize my results.

### 5.1 Model 1

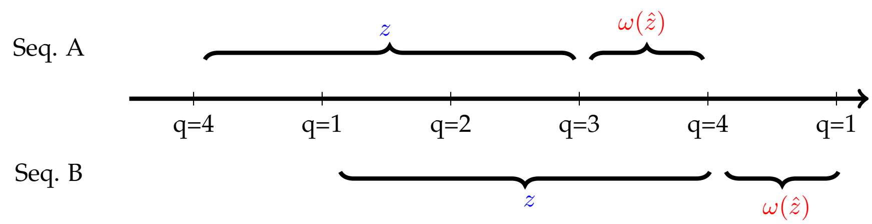
In the first model, my key independent variable, $\omega$, is the ratio of post-tax and pre-tax predicted earnings for household $i$ in period $q$. This net of tax wage rate is a function of household $i$'s earnings from the three previous quarters, $z$, and tax policy in year $y$ and state $s$.

I construct this measure by, first, summing each tax unit's earnings from the previous three quarters, and then identifying their tax liability assuming that sum equaled their total tax year earnings. I then assume each households' earnings in the next quarter equal their average earnings from the three previous quarters, and I recalculate their total tax liability for this new sum. The difference between these after-tax incomes, divided by the average of the to-date earnings, is the net of tax wage rate for the next period's income. It is the share of the next period's projected earnings that the household expects to retain after taxes. A positive one unit increase in this ratio equals a 100 percentage point increase in the ratio of post- and pre-tax income on the next quarter's predicted earnings.

$$\omega = \underbrace{\left(\frac{1}{3}z_{iyq}\right)^{-1}}_{\text{average to-date earnings}} \left( \underbrace{\left(1-\tau_{sy}\left(\frac{4}{3}z_{iyq}\right)\right)\frac{4}{3}z_{iyq}}_{\text{post-tax predicted quarter's earnings}} - \underbrace{\left(1-\tau_{sy}(z_{iyq})\right)z_{iyq}}_{\text{post-tax previous three quarter's earnings}} \right), \text{ where } z_{iyq} = \sum_{q=1}^{3} y_{iyq}$$

I construct this variable for every sequence of four consecutive quarters for which I can observe each tax unit's earnings. This means that I have four measures of $\omega$ and $z$ for each tax year, one for each quarter, for every tax unit. If I observe a household for three tax years, I have twelve observations for that household. Figure 1 illustrates how these sequences are constructed. Figure 11 shows the distribution of $\omega$ for all SIPP and SNAP households in the fourth quarter across the three tax years.

**Figure 1:** Model 1




**Notes.** Figure 1 illustrates how I construct simulated tax years. Each sequence of four consecutive quarters with earnings information is a simulated tax year, and I use the sum of the first three quarters' earnings in this simulated tax year to predict earnings in the next quarter. Note that Seq. B aligns with the true tax year.

I stack these sequences, and regress the log of actual earnings $y$ in quarter $q$ on the predicted net of tax wage rate $\omega$ in quarter $q$. I control for each household's earnings from the three preceding quarters, $z$, as well as state-by-year, household type and demographic fixed effects. The parameter $\beta$ is a measure of households' labor supply elasticity – the percent change in $y$ for a 100 percent change in predicted net of tax wage rate for that quarter.

$$\underbrace{\ln y_{iyq}}_{\text{log earnings}} = \beta\omega_{iyq} + \pi_q \underbrace{\omega_{iyq}\cdot Q}_{\text{predicted net of tax wage rate}\times\text{quarter dummy}} + \gamma \underbrace{\ln z_{iyq}}_{\text{log sum of last three quarters' earnings}} + \underbrace{\alpha_i}_{\text{household fixed effect}} + \underbrace{\theta_{ys} + \theta_h + \theta_x}_{\text{year}\times\text{state, household type, demographic fixed effects}} + \varepsilon_{iyq} \quad (2)$$

Since $\omega$ is a function of previous earnings and despite controlling for $z$, estimates of $\beta$ are confounded by serial correlation between earnings and lagged earnings. Households with lower past earnings are likely to have lower future earnings. Moreover, the correlation between past and future earnings likely varies over levels of $z$ and $\omega$. For example, households with especially low $z$ or high $\omega$ may exhibit higher future earnings if they are reverting back to average earnings level or working to achieve a certain minimal level of earnings.

I account for these concerns by interacting $\omega$ with an indicator for calendar quarter, $Q$, and assessing whether this response varies across the tax year. The coefficient on this interaction, $\pi$, captures the unique relationship between $y$ and $\omega$, or the excess sensitivity of $y$ to $\omega$, in calendar quarters 2, 3 and 4 relative to quarter 1. If serial correlation in earnings does not have a systematic seasonal pattern, then each $\pi_q$ should equal zero. If households adjust earnings to predicted tax incentives when those incentives are more binding at year's end, then $\pi_{q=4}$ will be positive. Indeed, my preferred estimate of labor supply elasticity will be my estimate of $\pi_{q=4}$. This coefficient identifies the relationship between log earnings and predicted net of tax wage rate in the fourth quarter, netting out the standard period-to-period relationship between past and future earnings captured by $\beta$.

I estimate four variations of Equation 2. First, I re-estimate Equation 2, but replace the continuous measure of $\omega$ with twelve levels of $\omega$. I group households into those with $\omega$ less than .55, greater than 1.1, and increments of .05 in between. The linear parameters $\pi_q$ mask important heterogeneity in the response across both earnings and values of $\omega$, and estimates from Equation 3 capture whether responses estimated in Equation 2 are driven by households facing particular levels of $\omega$.

$$\ln y_{iyq} = \beta \Omega_{iyq} + \pi_{q\omega} \Omega_{iyq} \cdot Q + \gamma \ln z_{iyq} + \alpha_i + \theta_{ys} + \theta_h + \theta_x + \epsilon_{iyq} \tag{3}$$

Second, I replaced binned values of $\omega$ with binned values of predicted annual income, $Z$. I use earnings from the previous three quarters to predict income in the next quarter, and then group households into \$2,000 bins of predicted total income over the four quarters. I interact the binned values with indicators for calendar quarter 2, 3 and 4.

$$\ln y_{iyq} = \beta Z_{iyq} + \pi_{qz} Z_{iyq} \cdot Q + \alpha_i + \theta_{ys} + \theta_h + \theta_x + \epsilon_{iyq} \tag{4}$$

Third, I re-estimate Equation 2 but replace $\omega$ with households' predicted marginal tax rate on the first dollar earned in the subsequent quarter. Fourth, I replace the log earnings with log hours.

### 5.2 Model 2

In the previous model, I assume workers understand their final period's net of tax wage rate only after realizing their likely annual income. In actuality, households have more information about what their true tax rate is likely to be even if they are ignorant of their future earnings. Households can make reasonable estimates of their annual income and their likely net of tax wage rate on January 1st using other person information, some of which is observed by the researchers (e.g., household type, state, year, occupation, age) while other is not (e.g., full work histories, preferences, understandings of their local labor market, or agreements with employers).

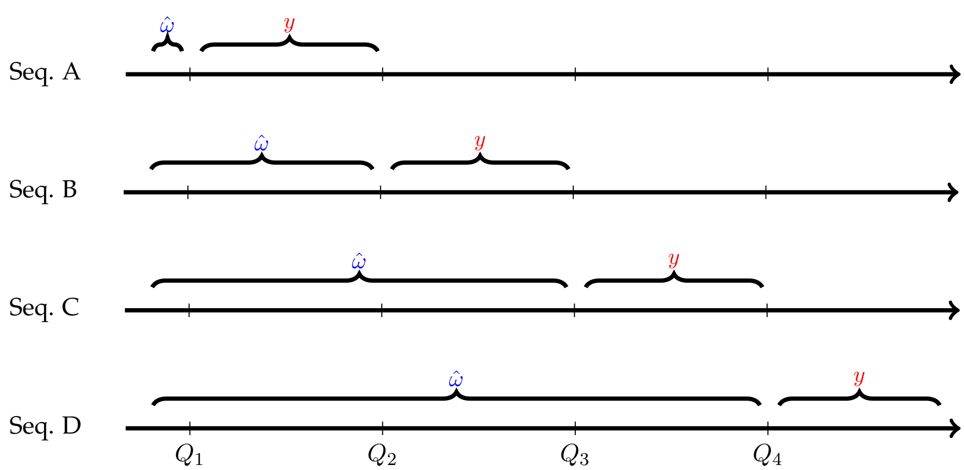
Recall that each households' marginal tax rate at the end of the tax year is, in fact, the marginal tax rate applied to each dollar they earned across the tax year. If workers can project what tax rate will apply to their fourth quarter earnings, they might choose to adjust their labor supply earlier in the year. Accordingly, as expectation of one's true $\omega$ change, workers might make continual adjustments to their labor supply.

I test whether households exhibit this behavior. I estimate the relationship between labor supply in each calendar quarter, $y_q$, and year-end net of tax wage rate $\omega_{q=4}$. I instrument for each household's $\omega_{q=4}$ with similar household's actual $\omega_q = 4$. I regress each households' actual $\omega_{q=4}$ on a vector of household characteristics (age, race, gender, state, year) and their predicted year-end income given their to-date earnings within the tax year, $\tilde{z}$, as of four different periods: the start of Q1, the end of Q1, the end of Q2 and the end of Q3.

$$\underbrace{\omega_{iy,q=4}}_{\substack{\text{household } i\text{'s} \\ \text{true } \omega_{q=4} \\ \text{in year } y}} = \underbrace{\tilde{z}_{iyq}}_{\substack{\text{earnings as of} \\ \text{the start of} \\ \text{qtr } q \text{ in year } y}} + \underbrace{\theta_{ys} + \theta_h + \theta_x}_{\substack{\text{year} \times \text{state,} \\ \text{household type,} \\ \text{demographics}}} + \epsilon_{iyq} \tag{5}$$

I use coefficients from Equation 5 to predict each tax unit's year-end $\hat{\omega}$ as of each period. Thenm, I estimate a model similar to Equation 2 using $\hat{\omega}$. Since households have no earned income as of the beginning of the tax year, I do not include a control for earnings when predicting $\omega$ at the start of the tax year.

**Figure 2:** Model 2 sequences




**Notes.** Figure 2 illustrates the sequences for which I identify $\hat{\omega_q}$. In Seq. A, I use non-earnings information observable before the tax year begins, including indicators for filing status by number of dependents, year by state, and demographic characteristics. I identify the household's likely $\omega_{q=4}$ from these variables, and then identify whether $y_{q=1}$ positively covaries with this prediction. In Seq. B, I use the same information as in Seq. A and add in predicted earnings information form quarter 1, and so on.

Having identified $\hat{w}$ for each tax unit at of the start of each quarter $q$, I can then estimate

Equation 6.

$$\ln y_{iyq} = \beta\hat{\omega}_{iy,q=4} + \pi_q\hat{\omega}_{iy,q=4} \cdot Q + \gamma \ln z_{iyq} + \alpha + \theta_{ys} + \theta_h + \theta_x + \varepsilon_{iyq} \tag{6}$$

As in Equation 2, I control for the log of the three previous quarter's earnings to account for dynamic earnings processes. The coefficient, $\pi$, on the interaction of $\omega$ and the quarter $Q$, identifies whether there is a separate effect of one's expected year-end net of tax wage rate on next one's earnings in the following quarter. If workers can forecast their year-end $\omega_q = 4$ accurately, we might expect each value of $\pi_q$ to be zero; households can still respond to their tax incentives but that response does not have to principally occur at year's end. Households might gain greater clarity of their true $\omega$ as the year progresses, but households could adjust labor supply in the present according to a reasonable estimate of their year-end tax rate.

# 6 Results

## 6.1 Main Results

Table 5 and Table 6 summarize estimates of $\beta$ and $\pi$ across different versions of Equation 2 among SIPP and SNAP households, respectively. Though magnitudes differ, overall patterns are similar in both samples. When I do not account for $z$, I find that households with higher $\omega$ have lower earnings in the subsequent quarter, which captures the serial correlation issue raised above: households with lower past earnings are expected to continue to have low earnings, despite their high $\omega$. If I include $z$ but only account for heterogeneity across households by controlling for demographics, household type and state by year effects, $\theta_x$, $\theta_h$, and $\theta_{ys}$. I find almost no relationship between short-term tax incentives and earnings response. When I include a household fixed effect, $\alpha$, I recover the predicted pattern. When the same household faces a higher $\omega$, they tend to earn more in the next period, and this relationship is strongest at year's end, when $\omega$ is most binding. Recall that my preferred estimate of the intensive margin labor supply elasticity is captured by $\pi_{q=4}$; this parameter identifies the excess sensitivity of earnings to $\omega$ at the real end of the tax year, netting out the period-to-period relationship between earnings levels captured by $\beta$. In the SIPP, I estimate intensive marginal labor supply elasticity to be .08. Among SNAP households, I estimate the same elasticity to be .18.

Figure 12 plots estimates of $\pi_{q\omega}$ from Equation 3. The positive relationship between earnings and the predicted net of tax wage rate is driven largely by households facing an $\omega$ greater than one, and that this relationship is strongest in the fourth quarter. These response is observable in both samples, though it's strongest in the larger SNAP sample, where earnings are measured with greater accuracy and there are a greater share of households with especially low earnings.

Figure 13 plots estimates from Equation 4 and further illustrate that this response is largely driven by incentives created by the EITC. I overlay these estimates on the EITC schedule for single filers with two dependents in 2017. For Panel B, I use the combined federal and state EITC schedule. The non-linear relationship between $\ln y$ and levels of predicted income, $Z$, suggest that households who expect to be in the phase-in range of the EITC are especially likely to increase earnings in the following quarter. That this effect is particularly pronounced in the fourth quarter suggests it is a response to tax incentives and not due to other serial patterns, like mean reversion.

Table 7 and Table 8 summarize estimates from Equation 6. Results are similar across the four models since $\omega$ is a function of these controls. Despite the alternative definition of $\omega$, my results are quite similar to those from Model 1. It remains the case that households tend to increase their labor supply when they expect to face a positive $\omega$ and this response is strongest at the end of the year.

## 6.2 Supplementary Results

### 6.2.1 Response to Marginal Tax Rate

I estimate another version of Equation 2 wherein I use households' predicted combined federal and state marginal income tax rate as my independent variable. Results from this estimation are summarized in Table 9 and Table 10. In the SIPP, I find no relationship between earnings and marginal tax rate. In every model, the effect is near zero. This is likely due to my SIPP sample having too few households with low enough earnings to face steeply negative tax marginal rates. My preferred estimate in the SNAP sample, however, recovers the expected negative relationship, and the effect is again clearest at the end of the year. The response is much more limited, which suggests that households are more responsive to their expected average tax rate.

### 6.2.2 Change in Hours Worked

Next, I estimate Equation 2, but use log hours as my outcome variable as opposed to log earnings. I only observe reported hours in the SIPP, meaning I can only estimate this response in that sample. Still, hours are only reported as the average over a representative week in the calendar month. Table 11 summarize those results. Results are similar as those for earnings, but I cannot rule out that the fourth quarter response is the same as the response as the second or third quarter. I interpret these findings to suggest that labor supply plays a role in the earnings elasticity reported in Table 5, but measurement issues make it difficult to draw a strong conclusion.

### 6.2.3 Subgroups

I test whether these responses vary by filing status and presence of dependents. Estimates from analyses within these subgroups are summarized in Table 12 and Table 13. I find that married households are more sensitive to their predicted net of tax wage at year's end, which is consistent with previous literature. Results differ between the SIPP and administrative data for households with or without children.

Table 14 summarizes results from additional estimates of Equation 2 restricting to the following subgroups in the SIPP.

- **Only hourly workers.** We would expect response to be clearest among hourly workers, since they are more subject to scheduling volatility and have greater flexibility in adjusting shifts and schedules in a particular quarter. Column 1 in Table 14 presents estimates of Equation 2 limited to households in which the head or spouse is an hourly worker. Though the effec is slightly higher, the estimates are not dramatically different.

- **Self-employed workers.** Saez (2010) shows that taxable income elasticity is highest among self-employed workers, who exhibit the greatest bunching at the first kink-point in the EITC schedule. To test whether this behavior is due to a true earnings response or tax manipulation, I estimate my model among the small number of households in my SIPP sample in which a head or spouse reports having some self-employment earnings in the tax year. I find that the response to year-end tax incentives is indeed much higher among households with a self-employed individual; my estimate of $\pi_{q=4}$ is .24, which is three times larger than the primary result reported in Table 5. However, when I test whether that response is driven by changes in self-employed earnings, the effect disappears (Column 3). Since the bunching Saez documents in his study is driven by Schedule C income, I do not interpret these results as overturning his conclusion that bunching by self-employed individuals is driven by manipulation as opposed to a true earnings response. At the same time, my sample size is small and there are reasonable concerns about measurement of self-employment earnings in the SIPP.

- **Dropping retail workers.** One concern with my approach is that there are significant changes in labor demand, as well as supply, around national holidays that occur at the end of the calendar year. For example, if lower-wage retail employees are more likely to work overtime, receive higher wages, or work more frequent shifts in the holiday season, this increase in earnings could bias my result. I should account for this concern by controlling for occupational fixed effects in the SIPP, and household and worker fixed effects in both datasets. To the extent those concerns remain, however, I also re-estimate Equation 2 in the SIPP excluding retail workers entirely from the sample. My results do not change.

#### 6.2.4 Dynamic Panel Bias

My approach raises standard concerns with studies involving dynamic panels and lagged dependent variables. Even though neither of my models include an actual lagged value of $y$ as a regressor, both $\omega$ and $z$ are functions of lagged values of $y$. My preferred estimate in Model 1 involves controlling for panel fixed effects, which risks introducing a mechanical relationship between the lagged dependent variable and the error term, biasing my estimated coefficients on $\omega$ and $\ln(z)$ (Nickell, 1981).

Alternative models account for heterogeneity across households without using fixed effects. However, estimating these models in my setting presents some challenges. First, available tools for implementing the GMM estimators assume the endogenous term is a single lagged dependent variable. My approach involves five separate endogenous regressors: $\omega$ and the interactions with each calendar quarter, plus $z$, the log of the three quarters' earnings. Instrumenting for each of these variables with their lagged levels and differences yields not only a proliferation of instruments, but also involves differencing lagged values across tax years, as opposed to subsequent quarters. Second, even though I have information about earnings for up to twelve periods for some households, I am interested in the unique effect in particular calendar quarters. This means I only have a maximum of three periods for each household. GMM estimators are more useful when more past and future realization of the dependent variable are available.

Notwithstanding these issues, I estimate the Anderson-Hsiao estimator, which recommended estimators which does not require using multiple lagged and future values of the dependent variable(Anderson and Hsiao, 1982).[6] I estimate this via two-stage least squares. I instrument for $\Delta\omega_{iyq}$ and $\Delta \ln z_{iyq}$ – the difference between each household's value of $\omega$ and $\ln z$ in the final tax year and the value from the penultimate tax year – with the furthered lagged values of $\omega_q$ and $ln_z$.

$$\Delta\omega_{iyq} = L_8\omega_{iyq} + \theta_{ys} + \theta_h + \theta_x + \varepsilon_{iyq}$$
$$\Delta \ln z_{iyq} = L_8 \ln z_{iyq} + \theta_{ys} + \theta_h + \theta_x + \varepsilon_{iyq}$$

I then relate the first difference between $\ln y_{iyq)}$ in the final and previous period with the instrumented values of $\Delta\omega_{iyq}$ and $\Delta \ln z_{iyq}$.

$$\Delta \ln y_{iyq} = \pi_q\tilde{\omega}_{iyq} + \gamma\tilde{\ln} z_{iyq} + \theta_{ys} + \theta_h + \theta_x + v_{iyq} \tag{7}$$

Table 15 summarizes the results from this estimation among SIPP and SNAP households. The results differ from my primary estimation. Among SNAP households, it remains the case that even instrumented earnings tend to increase as the tax year progresses, but the largest response now appears in the third quarter as opposed to the fourth, but these estimates are noisy. Among SIPP households, my estimates are dramatically different. The earnings response are substantially lower in the fourth quarter, the opposite of my main result. But none of my

[6] The "Difference GMM" and "Systems GMM" estimators promise increased efficiency over the Anderson-Hsiao estimator by leveraging additional information about the evolution pf the lagged dependent variable from additional past of future values of that variable. Given my short panel, I am unable to implement these more popular estimators.

estimates are statistically significant. In addition to the lack of statistical significance, and all of the issues about applying this estimator in my setting, there are other reasons to be cautious in interpreting these results. First, I fail the over-identification test in both versions. Second, Bond (2002) points out that that the proper estimate should fall between the biased estimates in the the OLS and the fixed effects models. All of my estimates in the SIPP sample, and all but my estimate of $\gamma$ in the SNAP sample, are outside these bounds, suggesting my instruments are not valid.

# 7 Conclusion

This paper studies the impact of tax policy on household labor supply using differences in uncertainty about annual income and tax incentives. Using survey and administrative data, I document significant within and cross year variation in household earnings and implied tax rates on those earnings. I use the fact that uncertainty about tax rates is resolved over the course of the tax year to identify the effect of tax policy on labor supply. I relate household earnings in the final quarter of the tax year to the share of the households' predicted earnings they expect to retain. I distinguish this response to tax incentives from standard serial correlation in earnings by comparing this response to other simulated tax years, and I use household fixed effects to control for omitted variable bias. I interpret excess sensitivity to predicted net of tax wage rate in the fourth quarter to represent households' earnings elasticity. I conclude that households exhibit a small but non-zero intensive marginal response to tax policy. My preferred estimate of the intensive margin earnings elasticity is between .06 and .18. Finally, I conclude that this effect is driven largely by the steeply negative tax rates created by the phase-in part of the EITC.

This study makes an important contribution to the academic literature studying labor supply response to tax policy. The most common approaches to identifying intensive marginal labor supply elasticity suffer from important identification challenges, which my approach overcomes. Leveraging unique panel data, I identify how the same household adjust earnings when tax incentives change within and across tax years. I conclude labor supply elasticity is small, consistent with the rest of the micro literature.

This study also has at least two practical policy implications. First, I document how income variation results in changes to household tax incentives, predicted tax liabilities, and likely tax refunds. This provides useful guidance to policymakers on two fronts. First, for policymakers interested in reforming the EITC to pay out benefits in advance of the tax filing season, I provide evidence about how likely those forecasts are likely to be wrong. Second, for policymakers interested in reaching out to likely eligible households or pre-filling their tax returns, I also provide evidence about how well within-year earnings can predict year-end EITC amounts, and for which households these forecasts are most likely to be wrong.

The second practical policy implicates has to do with potential reforms to the structure of the EITC itself. The argument for structuring the EITC with a phase-in is that the negative tax rate should increase affected household's intensive margin labor supply via the substitution effect, minimization negative labor supply distortions driven by an income effect. If the program does not have this effect, however, it suggest the effect of denying more assistance to the lowest-income households is not justified. This paper provides evidence that the EITC's does increase labor supply, as intended. Whether this pro-work effect warrants limiting redistribution to the lowest income household, and whether a basic credit could be incorporated into current policy, is left to future work. I also find limited evidence that households facing steeply positive marginal tax rates reduce their labor supply. This finding suggests that concerns about significant work disincentives created by some means-tested programs for a small subset of workers is not warranted.

One concern with this study is I do not account for the tax incentives created by benefit schedules of means-tested programs. Programs like SNAP reduce benefits when household earnings reach a particular level. Like positive income tax rates, reductions in benefits could affect labor supply decisions. If program enrollment exhibits systemic seasonal patterns, this could bias my results. This is a testable concern, however, and one I can address in future work.

## References


Altonji, J. G. (1986). Intertemporal substitution in labor supply: Evidence from micro data. *Journal of Political Economy*, 94(3, Part 2):S176–S215.

Anderson, T. W. and Hsiao, C. (1982). Formulation and estimation of dynamic models using panel data. *Journal of Econometrics*, 18(1):47–82.

Angrist, J. D. (1991). Grouped-data estimation and testing in simple labor-supply models. *Journal of Econometrics*, 47(2-3):243–266.

Bhargava, S. and Manoli, D. (2015). Psychological frictions and the incomplete take-up of social benefits: Evidence from an irs field experiment. *American Economic Review*, 105(11):3489–3529.

Blomquist, S. and Newey, W. (2017). The bunching estimator cannot identify the taxable income elasticity. Technical report, National Bureau of Economic Research.

Blundell, R., Brewer, M., Haan, P., and Shephard, A. (2009). Optimal income taxation of lone mothers: an empirical comparison of the UK and Germany. *The Economic Journal*, 119(535):F101–F121.

Blundell, R., Duncan, A., McCrae, J., and Meghir, C. (2000). The labour market impact of the Working Families' Tax Credit. *Fiscal Studies*, 21(1):75–104.

Blundell, R. and MaCurdy, T. (1999). Labor supply: A review of alternative approaches. In *Handbook of labor economics*, volume 3, pages 1559–1695. Elsevier.

Blundell, R., Pistaferri, L., and Saporta-Eksten, I. (2016). Consumption inequality and family labor supply. *American Economic Review*, 106(2):387–435.

Bond, S. R. (2002). Dynamic panel data models: a guide to micro data methods and practice. *Portuguese economic journal*, 1(2):141–162.

Burtless, G. and Hausman, J. A. (1978). The effect of taxation on labor supply: Evaluating the Gary negative income tax experiment. *Journal of Political Economy*, 86(6):1103–1130.

Camerer, C., Babcock, L., Loewenstein, G., and Thaler, R. (1997). Labor supply of New York City cabdrivers: One day at a time. *The Quarterly Journal of Economics*, 112(2):407–441.

Card, D. and Hyslop, D. R. (2005). Estimating the effects of a time-limited earnings subsidy for welfare-leavers. *Econometrica*, 73(6):1723–1770.

Chetty, R., Friedman, J. N., Olsen, T., and Pistaferri, L. (2011). Adjustment costs, firm responses, and micro vs. macro labor supply elasticities: Evidence from danish tax records. *The Quarterly Journal of Economics*, 126(2):749–804.

Chetty, R., Friedman, J. N., and Saez, E. (2013). Using differences in knowledge across neighborhoods to uncover the impacts of the eitc on earnings. *American Economic Review*, 103(7):2683–2721.

Chetty, R. and Saez, E. (2013). Teaching the tax code: Earnings responses to an experiment with EITC recipients. *American Economic Journal: Applied Economics*, 5(1):1–31.

Crawford, V. P. and Meng, J. (2011). New York City cab drivers' labor supply revisited: Reference-dependent preferences with rational-expectations targets for hours and income. *American Economic Review*, 101(5):1912–32.

Edin, K., Tach, L., and Halpern-Meekin, S. (2014). Tax code knowledge and behavioral responses among eitc recipients: Policy insights from qualitative data. *Journal of Policy Analysis and Management*, 33(2):413–439.

Eissa, N. and Hoynes, H. W. (2006). Behavioral responses to taxes: Lessons from the eitc and labor supply. *Tax policy and the economy*, 20:73–110.

Eissa, N. and Liebman, J. B. (1996). Labor supply response to the Earned Income Tax Credit. *The Quarterly Journal of Economics*, 111(2):605–637.

Farber, H. S. (2008). Reference-dependent preferences and labor supply: The case of New York City taxi drivers. *American Economic Review*, 98(3):1069–82.

Feenberg, D. and Coutts, E. (1993). An introduction to the taxsim model. *Journal of Policy Analysis and management*, 12(1):189–194.

Fehr, E. and Goette, L. (2007). Do workers work more if wages are high? evidence from a randomized field experiment. *American Economic Review*, 97(1):298–317.

Feldman, N. E., Katuščák, P., and Kawano, L. (2016). Taxpayer confusion: Evidence from the child tax credit. *American Economic Review*, 106(3):807–35.

Gelber, A. M., Jones, D., and Sacks, D. W. (2020). Estimating adjustment frictions using nonlinear budget sets: Method and evidence from the earnings test. *American Economic Journal: Applied Economics*, 12(1):1–31.

Gelber, A. M. and Mitchell, J. W. (2011). Taxes and time allocation: Evidence from single women and men. *The Review of Economic Studies*, 79(3):863–897.

Gerstel, N. and Clawson, D. (2018). Control over time: Employers, workers, and families shaping work schedules. *Annual Review of Sociology*, 44:77–97.

Golden, L. (2015). Irregular work scheduling and its consequences. *Economic Policy Institute Briefing Paper*, (394).

Grogger, J. (2003). The effects of time limits, the eitc, and other policy changes on welfare use, work, and income among female-headed families. *Review of Economics and Statistics*, 85(2):394–408.

Halpern-Meekin, S., Edin, K., Tach, L., and Sykes, J. (2015). *It's not like I'm poor: How working families make ends meet in a post-welfare world*. Univ of California Press.

Hausman, J. A. (1982). Labor supply. Technical report, National Bureau of Economic Research.

Hausman, J. A. (1985). Taxes and labor supply. In *Handbook of public economics*, volume 1, pages 213–263. Elsevier.

Heckman, J. J. and MaCurdy, T. E. (1980). A life cycle model of female labour supply. *The Review of Economic Studies*, 47(1):47–74.

Hotz, V. J. (2003). The Earned Income Tax Credit. In *Means-tested transfer programs in the United States*, pages 141–198. University of Chicago press.

Hotz, V. J. and Scholz, J. K. (2006). Examining the effect of the Earned Income Tax Credit on the labor market participation of families on welfare. Technical report, National Bureau of Economic Research.

Jones, D. (2010). Information, preferences, and public benefit participation: Experimental evidence from the advance eitc and 401 (k) savings. *American Economic Journal: Applied Economics*, 2(2):147–63.

Keane, M. and Moffitt, R. (1998). A structural model of multiple welfare program participation and labor supply. *International economic review*, pages 553–589.

Keane, M. and Rogerson, R. (2012). Micro and macro labor supply elasticities: A reassessment of conventional wisdom. *Journal of Economic Literature*, 50(2):464–76.

Keane, M. P. (2011). Labor supply and taxes: A survey. *Journal of Economic Literature*, 49(4):961–1075.

Kimball, M. S. and Shapiro, M. D. (2008). Labor supply: Are the income and substitution effects both large or both small? Technical report, National Bureau of Economic Research.

Kleven, H. J. and Waseem, M. (2013). Using notches to uncover optimization frictions and structural elasticities: Theory and evidence from pakistan. *The Quarterly Journal of Economics*, 128(2):669–723.

Laitner, J. and Silverman, D. (2005). Estimating life-cycle parameters from consumption behavior at retirement. Technical report, National Bureau of Economic Research.

Liebman, J. B. and Zeckhauser, R. J. (2004). Schmeduling.

Looney, A. and Singhal, M. (2006). The effect of anticipated tax changes on intertemporal labor supply and the realization of taxable income. Technical report, National Bureau of Economic Research.

Maag, E. (2019.). Using the EITC to help fight an economic slowdown. https://www.taxpolicycenter.org/taxvox/using-eitc-help-fight-economic-slowdown. Accessed: 2020-11-01.

Maag, E., Peters, H. E., Hannagan, A., Lou, C., and Siwicki, J. (2017). Income volatility: New research results with implications for income tax filing and liabilities. *The Urban Institute*.

MaCurdy, T., Green, D., and Paarsch, H. (1990). Assessing empirical approaches for analyzing taxes and labor supply. *Journal of Human resources*, pages 415–490.

MaCurdy, T. E. (1981). An empirical model of labor supply in a life-cycle setting. *Journal of Political Economy*, 89(6):1059–1085.

Manoli, D. and Weber, A. (2016). Nonparametric evidence on the effects of financial incentives on retirement decisions. *American Economic Journal: Economic Policy*, 8(4):160–82.

Martinez, I. Z., Saez, E., and Siegenthaler, M. (forthcoming). Intertemporal labor supply substitution?: Evidence from the Swiss income tax holidays. Technical report.

Meyer, B. D. and Rosenbaum, D. T. (2001). Welfare, the Earned Income Tax Credit, and the labor supply of single mothers. *The Quarterly Journal of Economics*, 116(3):1063–1114.

Miller, B. M., Mumford, K., et al. (2015). The salience of complex tax changes: evidence from the child and dependent care credit expansion. *National Tax Journal*, 68(3):477–510.

Moffitt, R. (1990). The econometrics of kinked budget constraints. *Journal of Economic Perspectives*, 4(2):119–139.

Nichols, A. and Rothstein, J. (2015). The Earned Income Tax Credit. In *Economics of Means-Tested Transfer Programs in the United States, Volume 1*, pages 137–218. University of Chicago Press.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the Econometric Society*, pages 1417–1426.

Pencavel, J. (1986). Labor supply of men: A survey. *Handbook of Labor Economics*, 1:3–102.

Pistaferri, L. (2003). Anticipated and unanticipated wage changes, wage risk, and intertemporal labor supply. *Journal of Labor Economics*, 21(3):729–754.

Powell, D. (2015). Do payroll taxes in the United States create bunching at kink points? *Michigan Retirement Research Center Research Paper*, (2015-327).

Powell, D. (2020). Does labor supply respond to transitory income? Evidence from the economic stimulus payments of 2008. *Journal of Labor Economics*, 38(1):1–38.

Rees-Jones, A. and Taubinsky, D. (2019). Measuring "Schmeduling". *The Review of Economic Studies*. rdz045.

Reichling, F. and Whalen, C. (2012). Review of estimates of the frisch elasticity of labor supply.

Rothstein, J. (2010). Is the EITC as good as an NIT? conditional cash transfers and tax incidence. *American Economic Journal: Economic Policy*, 2(1):177–208.

Saez, E. (1999). Do taxpayers bunch at kink points? Technical report, National Bureau of Economic Research.

Saez, E. (2010). Do taxpayers bunch at kink points? *American Economic Journal: Economic Policy*, 2(3):180–212.

Schneider, D. and Harknett, K. (2019). Consequences of routine work-schedule instability for worker health and well-being. *American Sociological Review*, 84(1):82–114.

Smeeding, T. M., Phillips, K. R., and O'Connor, M. (2000). The eitc: Expectation, knowledge, use, and economic and social mobility. *National Tax Journal*, pages 1187–1209.

Stafford, T. M. (2015). What do fishermen tell us that taxi drivers do not? an empirical investigation of labor supply. *Journal of Labor Economics*, 33(3):683–710.

Wilson, R. (2020). The EITC and employment transitions: Labor force attachment and annual exit. *National Tax Journal*, 73(1):11–46.

Yang, T.-T. (2018). Family labor supply and the timing of cash transfers: Evidence from the Earned Income Tax Credit. *Journal of Human Resources*, 53(2):445–473.

# 8 Tables

**Table 1:** Demographic characteristics for household head in SIPP sample

| | Full SIPP Sample | Wages>0 | Restricted Sample |
|---|---|---|---|
| | mean | mean | mean |
| Age | 45.9 | 41.5 | 39.6 |
| Female | 0.52 | 0.49 | 0.41 |
| Non-white | 0.19 | 0.19 | 0.21 |
| College grad | 0.33 | 0.36 | 0.34 |
| Married | 0.45 | 0.49 | 0.49 |
| Have kids | 0.63 | 0.72 | 0.52 |
| Annual wages (2017 $) | 28,432 | 36,506 | 43,827 |
| Observations | 274,899 | 214,287 | 134,594 |

**Notes.** Table 1 summarizes the average value for select characteristics of the primary filer in each SNAP household/tax unit pooled over the three tax years in our sample, 2015-2017. Wages are reported in 2017 dollars.

**Table 2:** Demographic characteristics for primary taxpayer in SNAP sample

| | SNAP + Tax Filer<br>mean | Wages>0<br>mean | Restricted Sample<br>mean |
|---|---|---|---|
| Age | 35.5 | 34.5 | 36.1 |
| Female | 0.57 | .58 | 0.67 |
| Non-white | 0.78 | .79 | 0.79 |
| Married | 0.19 | .20 | 0.14 |
| Have children | 0.53 | 0.59 | 0.79 |
| Annual wages ($) | 11,700 | 22,358 | 21,223 |
| Observations | 2,102,483 | 1,227,227 | 106,636 |

**Notes.** Table 2 summarizes the average value for select characteristics of the primary filer in each SNAP household/tax unit pooled over the three tax years in our sample, 2015-2017. Wages are reported in 2017 dollars.

**Table 3:** Share of households whose predicted income, average and marginal tax rates, and EITC amounts as of each quarter differ from their year-end actual values by more than identified ranges

| | $\|\hat{z} - z\| > \$5k$ | $\|\hat{\tau} - \tau\| > 10pp$ | $\|\widehat{\text{EITC}} - \text{EITC}\| > \$1k$ | $\|\widehat{\text{MTR}} - \text{MTR}\| > 10pp$ |
|---|---|---|---|---|
| | | **SIPP** | | |
| March | .28 | .06 | .13 | .15 |
| June | .18 | .03 | .03 | .11 |
| September | .06 | .01 | .01 | .06 |
| $\sigma$ | \$2,321 | 1.4 | \$93 | 2.5 |
| | | **SNAP** | | |
| March | .36 | .25 | .13 | .32 |
| June | .21 | .15 | .08 | .22 |
| September | .05 | .06 | .03 | .12 |
| $\sigma$ | \$2,651 | 4.1 | \$240 | 7.1 |

**Notes.** Table 3 summarizes the share of households in each sample, as of the end of each quarter, whose: (1) predicted annual income z is more than \$10,000 from their year-end income, (2) predicted annual tax rate $\tau$ is more than 10 percentage points from their actual year-end average tax rate, (3) predicted total EITC refund is more than \$1,000 from their year-end amount, and (4) predicted marginal tax rate is more than 10 pp from their year-end marginal tax rate. I limit to households who have positive earnings and no more than \$75,000 in annual income through each listed quarter. The final row reports the mean standard deviation for each predicted value over all tax units.

**Table 4:** Share of households whose predicted income, average and marginal tax rates, and EITC amounts as of each quarter differ from their year-end actual values by more than identified ranges

| | $\lvert \hat{z} - z \rvert > \$5k$ | $\lvert \hat{\tau} - \tau \rvert > 10pp$ | $\lvert \widehat{\text{EITC}} - \text{EITC} \rvert > \$1k$ | $\lvert \widehat{\text{MTR}} - \text{MTR} \rvert > 10pp$ |
|---|---|---|---|---|
| | | **SIPP** | | |
| Year over year | .46 | .13 | .08 | .23 |
| Min to max | .59 | .19 | .11 | .31 |
| $\bar{\sigma}$ | $6,298 | 5.70 | $210 | 5.35 |
| | | **SNAP** | | |
| Year over year | .46 | .41 | .27 | .44 |
| Min to max | .53 | .46 | .31 | .50 |
| $\bar{\sigma}$ | $4,818 | 9.57 | $620 | 12.6 |

**Notes.** Table 4 summarizes the share of households whose earnings, average and marginal tax rates, and EITC amounts in one year are particular values different from other years. In Row 1, I report the share of households whose (1) maximum annual income $z$ is more than $10,000 from their minimum year-end income, (2) maximum annual tax rate $\tau$ is more than 5 percentage points from their minimum year-end average tax rate, (3) maximum total EITC refund is more than $1,000 from their lowest EITC amount, and (4) maximum marginal tax rate is more than 10 pp from their lowest marginal tax rate. In Row 2, I report the same shares but compare differences between subsequent years, meaning I count households that appear in multiple tax years more than once in the denominator. I limit to households who have at least positive earnings and no more than $75,000 in annual income through each listed quarter. The final row reports the average standard deviation of each variable among households who appear for at least two tax years.

**Table 5:** Log earnings response in each quarter to predicted net of tax earnings, simulated using three previous quarters' earnings, SIPP sample

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $\ln y$ | $\ln y$ | $\ln y$ | $\ln y$ |
| $\omega$ | | | | |
| | -1.867*** | -1.908*** | 0.027 | -0.070 |
| | (0.029) | (0.030) | (0.017) | (0.047) |
| $\omega\times$ | | | | |
| Q2 | | | | |
| | 0.019*** | 0.019*** | 0.009 | 0.035*** |
| | (0.005) | (0.005) | (0.005) | (0.004) |
| Q3 | | | | |
| | 0.028*** | 0.027*** | 0.006 | 0.057*** |
| | (0.006) | (0.006) | (0.007) | (0.006) |
| Q4 | | | | |
| | 0.043*** | 0.043*** | 0.006 | 0.081*** |
| | (0.006) | (0.006) | (0.007) | (0.006) |
| z | | | | |
| | | | 0.883*** | 0.073*** |
| | | | (0.005) | (0.018) |
| Observations | 73239 | 73239 | 73239 | 73239 |
| Households | 12321 | 12321 | 12321 | 12321 |
| Demographics | | X | X | X |
| # of deps $\times$ marital status | | X | X | X |
| State $\times$ year | | X | X | X |
| Household FE | | | | X |
| $R^2$ | 0.24 | 0.38 | 0.70 | 0.81 |
| P-val from F-test | 0 | 0 | 0.790 | 0 |

**Notes.** Table 5 summarizes estimates of Equation 2 in the SIPP sample. Standard errors are clustered at the household-level, and I use household-level weights.

**Table 6:** Log earnings response in each quarter to predicted net of tax earnings rate in that quarter, simulated using three previous quarters' earnings, SNAP sample

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $\ln y$ | $\ln y$ | $\ln y$ | $\ln y$ |
| $\omega$ | | | | |
| | -1.165* | -1.368 | -0.001 | -0.051*** |
| | (0.004) | (0.004) | (0.007) | (0.009) |
| $\omega\times$ | | | | |
| Q2 | | | | |
| | 0.039 | 0.034*** | 0.015*** | 0.105*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Q3 | | | | |
| | 0.034 | 0.024*** | -0.008*** | 0.150*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Q4 | | | | |
| | 0.038 | 0.027*** | -0.015*** | 0.180*** |
| | (0.002) | (0.002) | (0.003) | (0.002) |
| $z$ | | | | |
| | | | 0.667*** | 0.040*** |
| | | | (.004) | (.006) |
| Observations | 703,792 | 703,792 | 703,792 | 703,791 |
| Households | 106,636 | 106,636 | 106,636 | 106,635 |
| Demographics | | X | X | X |
| # of deps × marital status | | X | X | X |
| State × year | | X | X | X |
| Household FE | | | | X |
| $R^2$ | 0.22 | 0.37 | 0.46 | 0.65 |
| P-val from F-test | 0.00 | 0.00 | 0.00 | 0.00 |

**Notes.** Table 6 summarizes results from estimations of Eq 2 in the SNAP sample. Standard errors are clustered at the household-level.

**Table 7:** Log earnings response in each quarter to predicted net of tax earnings rate in final quarter, SIPP sample

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $\ln y$ | $\ln y$ | $\ln y$ | $\ln y$ |
| $\hat{\omega}$ | | | | |
| | -4.032*** | -6.236*** | -1.525*** | -0.074 |
| | (0.041) | (0.045) | (0.057) | (0.041) |
| $\hat{\omega}$ | | | | |
| Q2 | | | | |
| | 0.003 | 0.017** | 0.019*** | 0.024*** |
| | (0.005) | (0.006) | (0.004) | (0.003) |
| Q3 | | | | |
| | 0.016** | 0.032*** | 0.014** | 0.037*** |
| | (0.006) | (0.007) | (0.005) | (0.004) |
| Q4 | | | | |
| | 0.003 | 0.057*** | 0.024*** | 0.055*** |
| | (0.006) | (0.007) | (0.005) | (0.004) |
| z | | | | |
| | | | 0.660*** | 0.126*** |
| | | | (0.008) | (0.010) |
| Observations | 102191 | 102168 | 102052 | 99458 |
| Households | 17840 | 17826 | 17826 | 15238 |
| Demographics | | X | X | X |
| # of deps × marital status | | X | X | X |
| State × year | | X | X | X |
| Household FE | | | | X |
| $R^2$ | 0.31 | 0.55 | 0.70 | 0.82 |
| P-val from F-test | 0 | 0 | 0.0300 | 0 |

**Notes.** Table 7 summarizes estimates of Equation 6 in the SIPP sample. Standard errors are clustered at the household-level, and I use household-level weights.

**Table 8:** Log earnings response in following quarter to predicted year-end net of tax earnings rate, SNAP sample

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $\ln y$ | $\ln y$ | $\ln y$ | $\ln y$ |
| $\hat{\omega}$ | | | | |
| | -2.312 | -2.941 | -1.639*** | -0.021* |
| | (0.007) | (0.008) | (0.009) | (0.010) |
| $\hat{\omega}\times$ | | | | |
| Q2 | | | | |
| | 0.138 | 0.152 | 0.101*** | 0.122*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Q3 | | | | |
| | 0.198 | 0.220 | 0.109*** | 0.161*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Q4 | | | | |
| | 0.225 | 0.251 | 0.112*** | 0.179*** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| z | | | | |
| | | | 0.352*** | 0.072*** |
| | | | (.003) | (.002) |
| Observations | 847,139 | 847,102 | 703,792 | 833,627 |
| Households | 135,871 | 135,856 | 135,856 | 125,926 |
| Demographics | | X | X | X |
| # of deps $\times$ marital status | | X | X | X |
| State $\times$ year | | X | X | X |
| Household FE | | | | X |
| $R^2$ | 0.18 | 0.35 | 0.41 | 0.61 |
| P-val from F-test | 0.00 | 0.00 | 0.00 | 0.00 |

**Notes.** Table 8 summarizes results from estimations of Eq 2 in the SNAP sample. Standard errors are clustered at the household-level.

**Table 9:** Log earnings response in each quarter to predicted federal and state marginal income tax rate, SIPP sample

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $\ln y$ | $\ln y$ | $\ln y$ | $\ln y$ |
| MTR | | | | |
| | 0.016*** | 0.016*** | -0.001*** | -0.001 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| MTR $\times$ | | | | |
| Q2 | | | | |
| | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Q3 | | | | |
| | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Q4 | | | | |
| | 0.002*** | 0.002*** | 0.002*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| z | | | | |
| | | | 0.885*** | 0.089*** |
| | | | (0.005) | (0.017) |
| Observations | 73239 | 73239 | 73239 | 73239 |
| Households | 12321 | 12321 | 12321 | 12321 |
| Demographics | | X | X | X |
| # of deps $\times$ marital status | | X | X | X |
| State $\times$ year | | X | X | X |
| Household FE | | | | X |
| $R^2$ | 0.19 | 0.33 | 0.70 | 0.81 |
| P-val from F-test | 0 | 0 | 0 | 0 |

**Notes.** **??** summarizes estimates from a version of Equation 2 in which I replace household's $\omega_q$ with the households' predicted marginal income tax rate in that quarter. Standard errors are clustered at the household-level, and I use household-level sampling weights.

**Table 10:** Log earnings response in each quarter to predicted federal and state marginal income tax rate, SNAP sample

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $\ln y$ | $\ln y$ | $\ln y$ | $\ln y$ |
| MTR | | | | |
| | 0.867*** | 0.891*** | -0.276*** | -0.004 |
| | (0.006) | (0.006) | (0.007) | (0.008) |
| MTR | | | | |
| Q2 | | | | |
| | 0.273*** | 0.274*** | 0.280*** | 0.012* |
| | (0.007) | (0.007) | (0.007) | (0.005) |
| Q3 | | | | |
| | 0.450*** | 0.444*** | 0.407*** | -0.016* |
| | (0.007) | (0.008) | (0.007) | (0.007) |
| Q4 | | | | |
| | 0.521*** | 0.505*** | 0.425*** | -0.020*** |
| | (0.008) | (0.007) | (0.007) | (0.007) |
| z | | | | |
| | | | 0.689*** | 0.098** |
| | | | (0.003) | (0.007) |
| Observations | 703815 | 703815 | 703815 | 703815 |
| Households | 106640 | 106640 | 106640 | 106639 |
| Demographics | | X | X | X |
| # of deps × marital status | | X | X | X |
| State × year | | X | X | X |
| Household FE | | | | X |
| $R^2$ | 0.21 | 0.32 | 0.43 | 0.63 |
| P-val from F-test | 0 | 0 | 0 | 0 |

**Notes.** **??** summarizes estimates from a version of Equation 2 in which I replace household's $\omega_q$ with the households' predicted marginal income tax rate in that quarter. Standard errors are clustered at the household-level.

**Table 11:** Log hours response in each quarter to predicted net of tax earnings, simulated using three previous quarters' earnings, SIPP sample

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $\ln y$ | $\ln y$ | $\ln y$ | $\ln y$ |
| $\omega$ | | | | |
| | -0.626*** | -0.597*** | -0.078** | -0.001 |
| | (0.024) | (0.024) | (0.027) | (0.030) |
| $\omega\times$ | | | | |
| Q2 | | | | |
| | 0.010* | 0.010* | 0.008 | 0.011** |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Q3 | | | | |
| | 0.011 | 0.011* | 0.006 | 0.015** |
| | (0.006) | (0.006) | (0.006) | (0.005) |
| Q4 | | | | |
| | 0.005 | 0.006 | -0.004 | 0.013* |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| z | | | | |
| | | | 0.238*** | 0.046** |
| | | | (0.008) | (0.014) |
| Observations | 70876 | 70876 | 70876 | 70817 |
| Households | 12224 | 12224 | 12224 | 12165 |
| Demographics | | X | X | X |
| # of deps $\times$ marital status | | X | X | X |
| State $\times$ year | | X | X | X |
| Household FE | | | | X |
| $R^2$ | 0.05 | 0.25 | 0.30 | 0.70 |
| P-val from F-test | 0.390 | 0.520 | 0.0600 | 0.580 |

**Notes.** Table 11 summarizes estimates of Equation 2 in the SIPP sample, but in which I replace the outcome variable with the log of the average hours worked per week, summed over the respective quarter. Standard errors are clustered at the household-level, and I use household-level weights.

**Table 12:** Log earnings response in each quarter to predicted net of tax earnings rate, simulated using three previous quarters' earnings, by household type, SIPP sample

| | Marital Status | | Presence of Children | |
|---|---|---|---|---|
| | (1) Single | (2) Married | (3) No Kid | (4) Have Kids |
| $\omega$ | | | | |
| | -0.077 | -0.044 | 0.101 | -0.052 |
| | (0.068) | (0.061) | (0.159) | (0.048) |
| $\omega\times$ | | | | |
| Q2 | | | | |
| | 0.020** | 0.054*** | 0.026*** | 0.044*** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Q3 | | | | |
| | 0.035*** | 0.086*** | 0.049*** | 0.067*** |
| | (0.008) | (0.008) | (0.007) | (0.009) |
| Q4 | | | | |
| | 0.062*** | 0.105*** | 0.073*** | 0.091*** |
| | (0.008) | (0.009) | (0.008) | (0.009) |
| z | | | | |
| | 0.046 | 0.095*** | 0.049 | 0.080*** |
| | (0.028) | (0.021) | (0.030) | (0.022) |
| Observations | 37539 | 35084 | 35751 | 37488 |
| Households | 6287 | 5925 | 6001 | 6420 |
| Demographics | X | X | X | X |
| # of deps $\times$ marital status | X | X | X | X |
| State $\times$ year | X | X | X | X |
| Household FE | X | X | X | X |
| $R^2$ | 0.84 | 0.76 | 0.82 | 0.81 |
| P-val from F-test | 0 | 0 | 0 | 0 |

**Notes.** Table 12 summarizes results from estimations of Eq 2 among married vs. single households and households with and without children in the SIPP sample. Standard errors are clustered at the household-level, and I use household-level weights.

**Table 13:** Log earnings response in each quarter to predicted net of tax earnings rate, simulated using three previous quarters' earnings, by household type, SNAP sample

| | Marital Status | | Presence of Children | |
|---|---|---|---|---|
| | (1) Single | (2) Married | (3) No Kid | (4) Have Kids |
| $\omega$ | | | | |
| | -0.058 | -0.031 | -0.194 | -0.039 |
| | (0.064) | (0.052) | (0.050) | (0.042) |
| $\omega\times$ | | | | |
| Q2 | | | | |
| | 0.102*** | 0.125*** | 0.157*** | 0.097*** |
| | (0.006) | (0.004) | (0.006) | (0.002) |
| Q3 | | | | |
| | 0.145*** | 0.180*** | 0.205*** | 0.143*** |
| | (0.007) | (0.005) | (0.007) | (0.002) |
| Q4 | | | | |
| | 0.178*** | 0.192*** | 0.229*** | 0.174*** |
| | (0.007) | (0.005) | (0.007) | (0.002) |
| z | | | | |
| | 0.041*** | 0.046*** | -0.029* | 0.048*** |
| | (0.005) | (0.016) | (0.026) | (0.007) |
| Observations | 602837 | 100692 | 149859 | 553956 |
| Households | 92599 | 13906 | 26984 | 82103 |
| Demographics | X | X | X | X |
| # of deps $\times$ marital status | X | X | X | X |
| State $\times$ year | X | X | X | X |
| Household FE | X | X | X | X |
| $R^2$ | 0.62 | 0.64 | 0.62 | 0.62 |
| P-val from F-test | 0 | 0 | 0 | 0 |

**Notes.** Table 13 summarizes results from estimations of Eq 2 among married vs. single households and households with and without children in the SNAP sample. Standard errors are clustered at the household-level.

**Table 14:** Earnings response in each quarter to predicted net of tax earnings rate, simulated using three previous quarters' earnings, by various subgroups, SIPP sample

| | (1) Hourly Workers | (2) Self-Employed | (3) Self-Emp earnings | (4) Drop Retail |
|---|---|---|---|---|
| $\omega$ | | | | |
| | -0.067 | 0.021 | 1.162 | -0.063 |
| | (0.044) | (0.270) | (2.060) | (0.048) |
| $\omega\times$ | | | | |
| Q2 | | | | |
| | 0.042*** | 0.132** | 0.053 | 0.035*** |
| | (0.005) | (0.048) | (0.398) | (0.005) |
| Q3 | | | | |
| | 0.067*** | 0.173** | -0.123 | 0.059*** |
| | (0.007) | (0.064) | (0.492) | (0.006) |
| Q4 | | | | |
| | 0.086*** | 0.261*** | 0.036 | 0.084*** |
| | (0.007) | (0.061) | (0.508) | (0.006) |
| z | | | | |
| | 0.039* | -0.366** | -0.872 | 0.069*** |
| | (0.020) | (0.130) | (0.894) | (0.018) |
| Observations | 54811 | 832 | 832 | 71571 |
| Households | 9485 | 178 | 178 | 12063 |
| Demographics | X | X | X | X |
| # of deps $\times$ marital status | X | X | X | X |
| State $\times$ year | X | X | X | X |
| Household FE | X | X | | X |
| $R^2$ | 0.81 | 0.82 | 0.42 | 0.81 |
| P-val from F-test | 0 | 0.0500 | 0.880 | 0 |

**Notes.** Table 14 summarizes estimates of Equation 2 for particular subsets of the SIPP sample. Column 1 reports estimated responses among households in which either the head or spouse report being an hourly worker. Column 2 reports estimates among households in which either the head or spouse report earnings any income from self employment in the tax year. Column 3 reports estimates among the same subset of self-employed workers, but I replace the outcome variable with the log of self-employment earnings, as opposed to all earned income. Column 4 reports estimates from the SIPP sample after I drop all households in in which either the head or spouse report working in the retail industry. Standard errors are clustered at the household-level, and I use household-level weights.

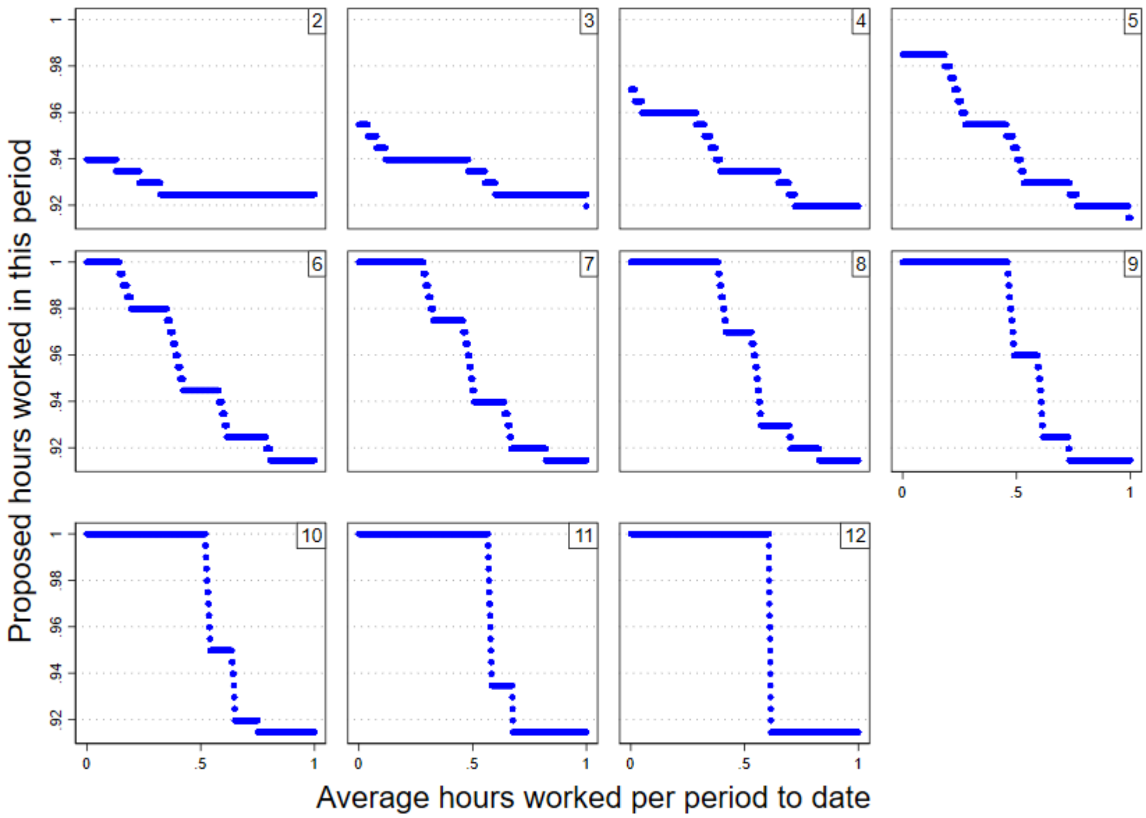
**Table 15:** Earnings response in each quarter to predicted net of tax earnings rate in that quarter, simulated using three previous quarters' earnings, SIPP and SNAP sample

| | SIPP | SNAP |
|---|---|---|
| $\tilde{\omega}_{q=1}$ | | |
| | 1.086* | -.381 |
| | (1.466) | (0.111) |
| $\tilde{\omega}_{q=2}$ | | |
| | 0.346 | 0.118*** |
| | (1.436) | (0.126) |
| $\tilde{\omega}_{q=3}$ | | |
| | 2.217 | 0.521*** |
| | (4.193) | (0.113) |
| $\tilde{\omega}_{q=4}$ | | |
| | -2.161 | 0.126*** |
| | (5.800) | (0.126) |
| $\tilde{z}$ | .977 | .630 |
| | (.312) | (.067) |
| Observations | 5,288 | 75,300 |
| Households | 1,322 | 18,825 |
| Demographic FE | X | X |
| Deps $\times$ Married | X | X |
| State $\times$ Year FE | X | X |
| Household FE | | |
| $R^2$ | 0.22 | 0.03 |
| P-val from F-test | 0.87 | 0.00 |
| Hansen J-stat | 0.00 | 0.00 |

**Notes.** Table 15 summarizes results from Equation 7. In both models, I cluster standard errors at the household-level. In the SIPP, I apply household weights.

# 9 Figures

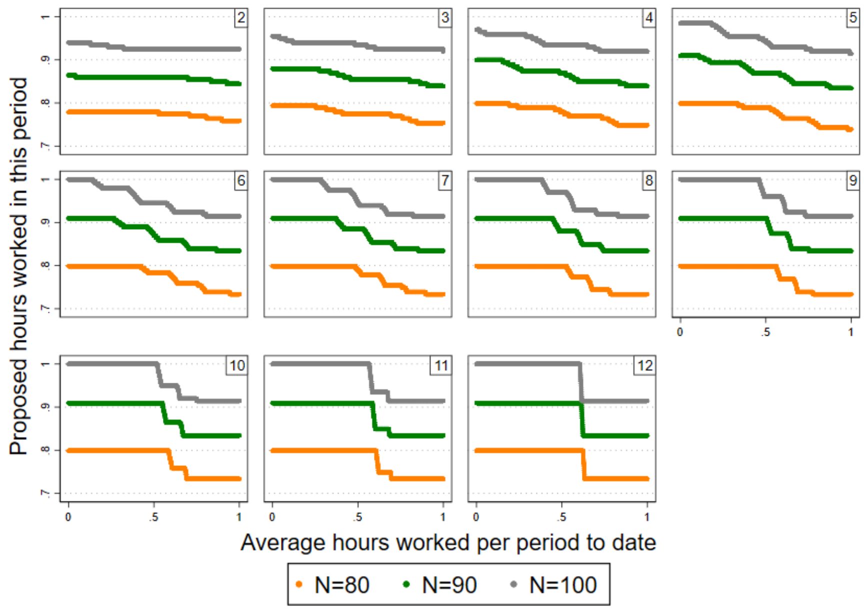
**Figure 3:** Agent's predicted hours choice based on average hours worked to date



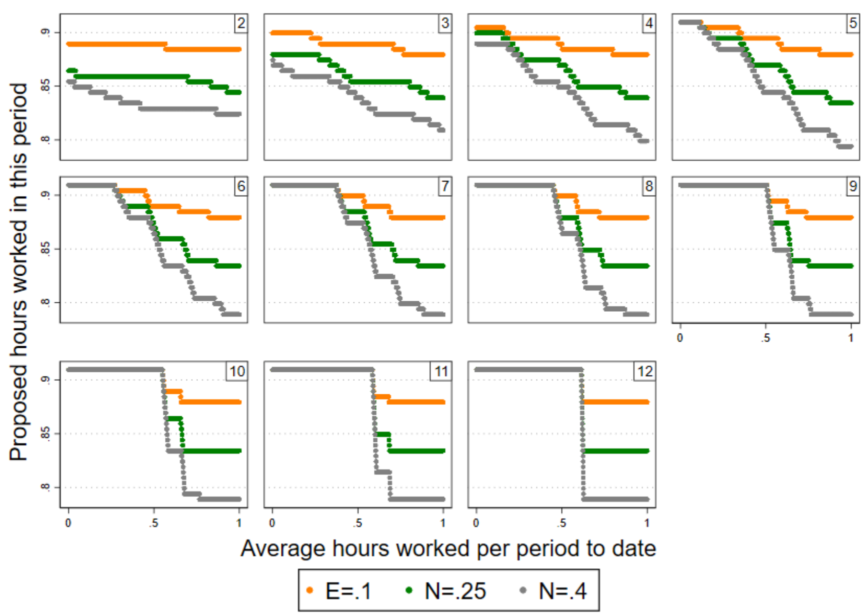

**Notes.** Figure 3 plots proposed hours in the subsequent period given average hours worked per period to date for a set of representative agents. In Panel A, I plot choices for three workers with different ability parameters $n$. These workers have the same elasticity $e = .3$ and face the same tax policy ($\tau_0 = 0, \tau_1 = .3$. In Panel B, I plot choices for three worker, all with $n = .9$, but with elasticities of .1, .25 and .4.

**Figure 4:** Agent's predicted hours choice based on average hours worked to date, by $n$ and $e$

**(a)** By ability $n$

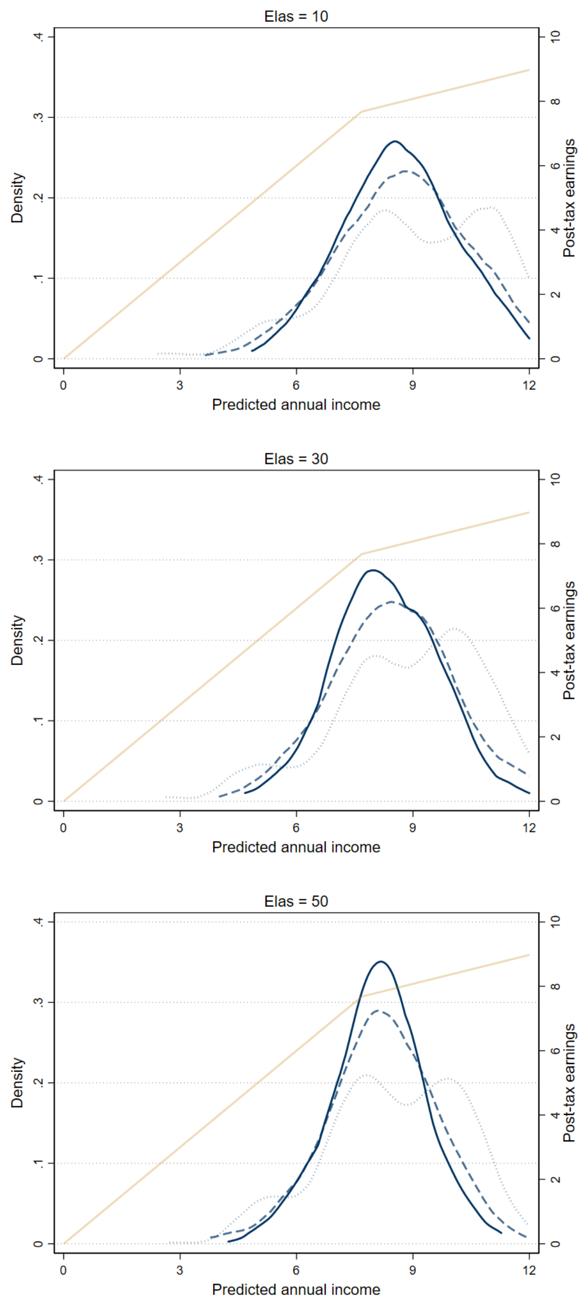



**(b)** By elasticity $e$




**Notes.** Figure 3 plots proposed hours in the subsequent period given average hours worked per period to date for a set of representative agents. In Panel A, I plot choices for three workers with different ability parameters $n$. These workers have the same elasticity $e = .3$ and face the same tax policy ($\tau_0 = 0, \tau_1 = .3$). In Panel B, I plot choices for three worker, all with $n = .9$, but with elasticities of .1, .25 and .4.

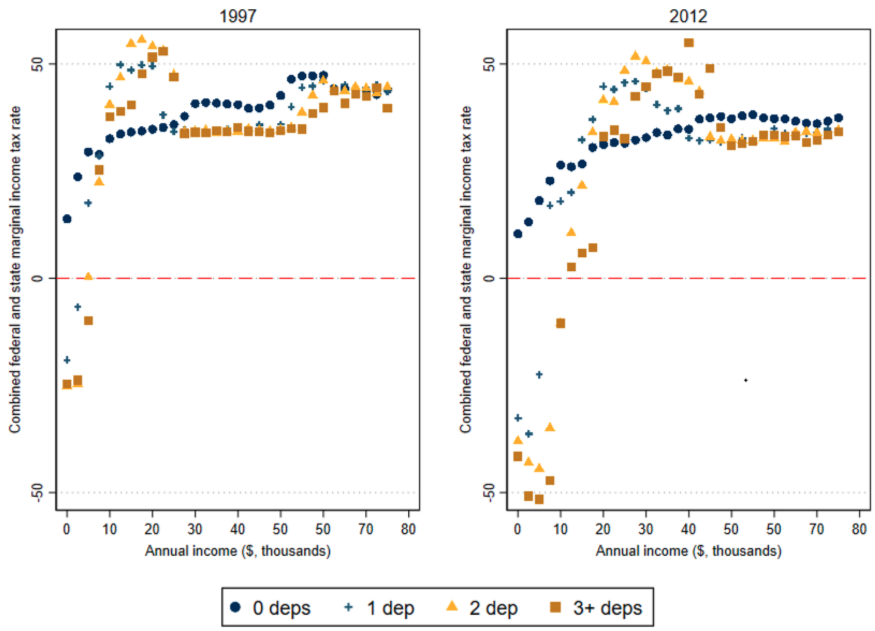
**Figure 5:** Distribution of proposed annual income as of three periods



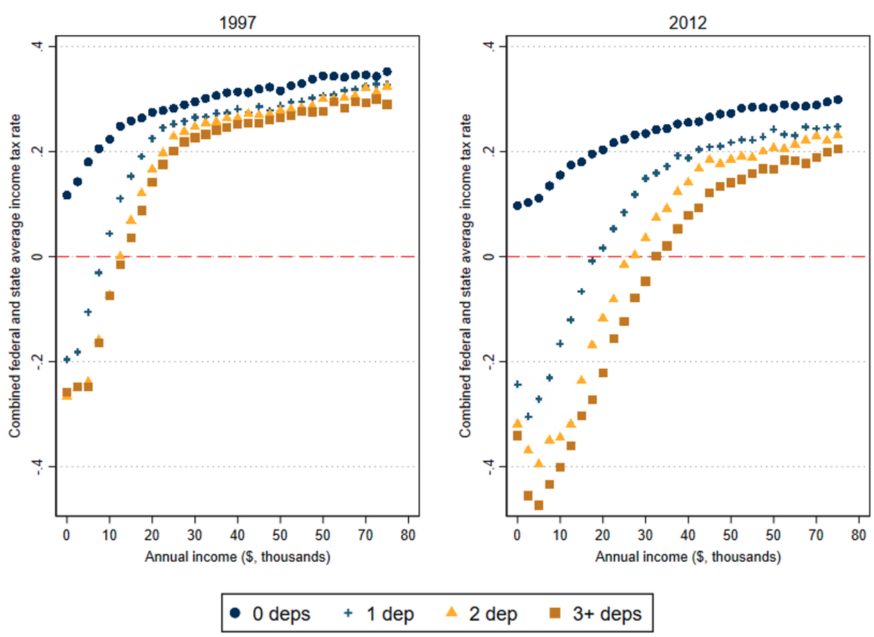

**Notes.** Figure 5 presents results from a three simulations of the model summarized in **??**. I plot the distributions of predicted annual income as of three periods for 500 agents with various levels of $n$. For each agent, I simulate responses using an elasticity $e$ of .1, .25 and .4. The other parameter values are: $p = .8, \tau_0 = 0, \tau_1 = .3$, and $z^* = 7.6$. The light dotted line indicates predicted earnings as of $d = 4$, the dashed line is as of $d = 8$, and the solid line is the last period, $d = 12$.

**Figure 6:** Combined marginal and average tax rates for married households, 1997 vs 2012, SIPP sample

**(a)** Marginal income tax rate



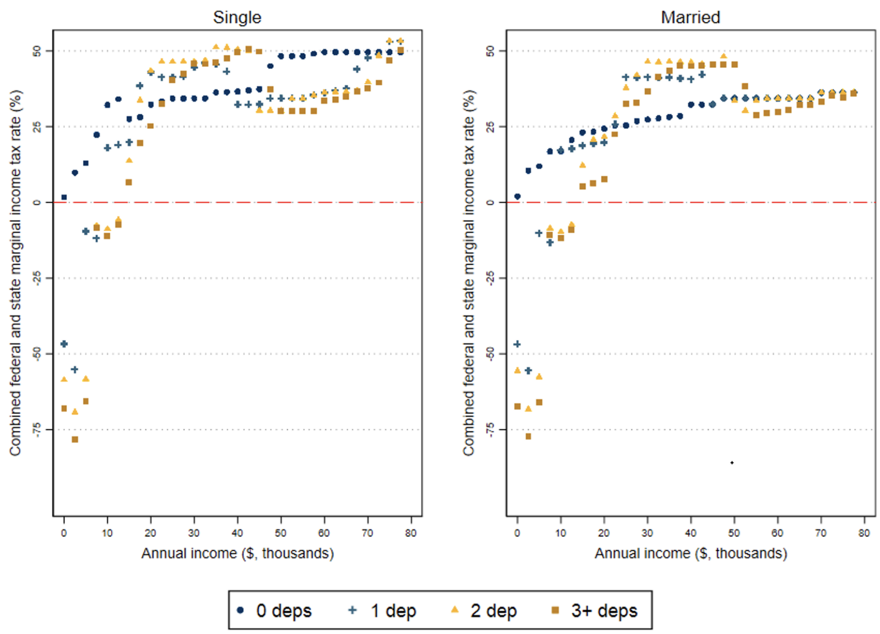

**(b)** Average income tax rate



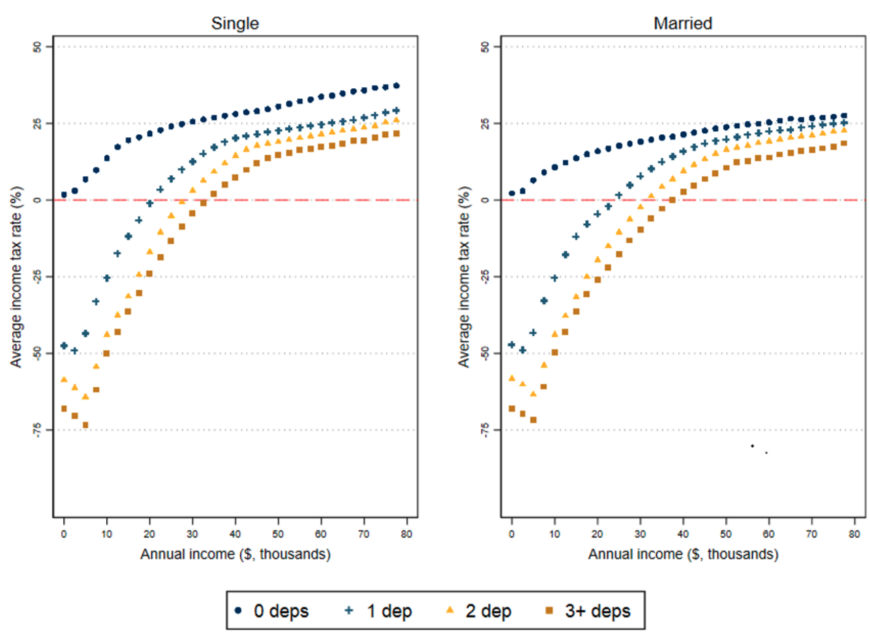

**Notes.** Figure 6 illustrates how marginal and average tax rates vary for married households with 0, 1, 2 or 3+ dependents in 1997 versus 2012. Within households with those dependents, I group households into annual income bins of $2,500. In each bin, I calculate the average and average marginal tax rate faced by households at year's end.

**Figure 7:** Combined marginal and average tax rates for married households, by number of dependents and annual income, CalFresh, 2017

**(a)** Marginal income tax rate



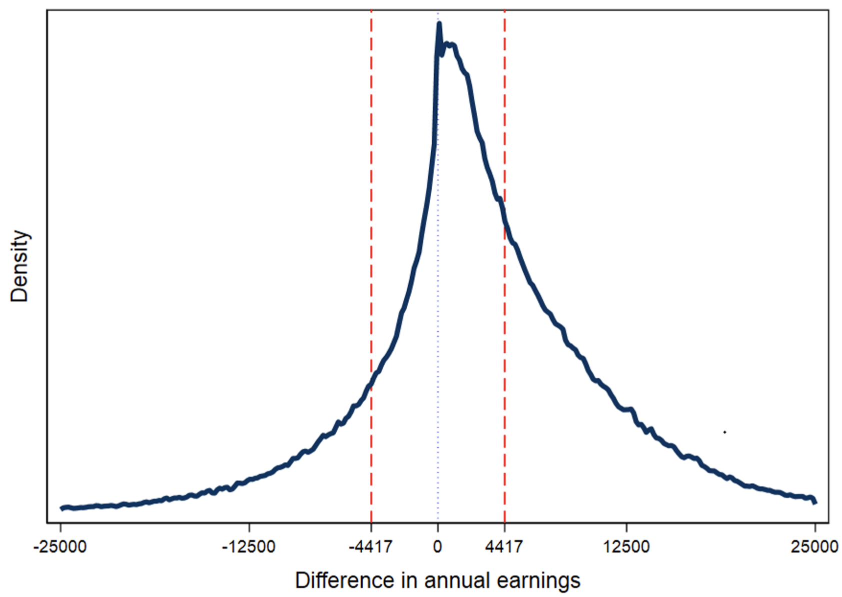

**(b)** Average income tax rate



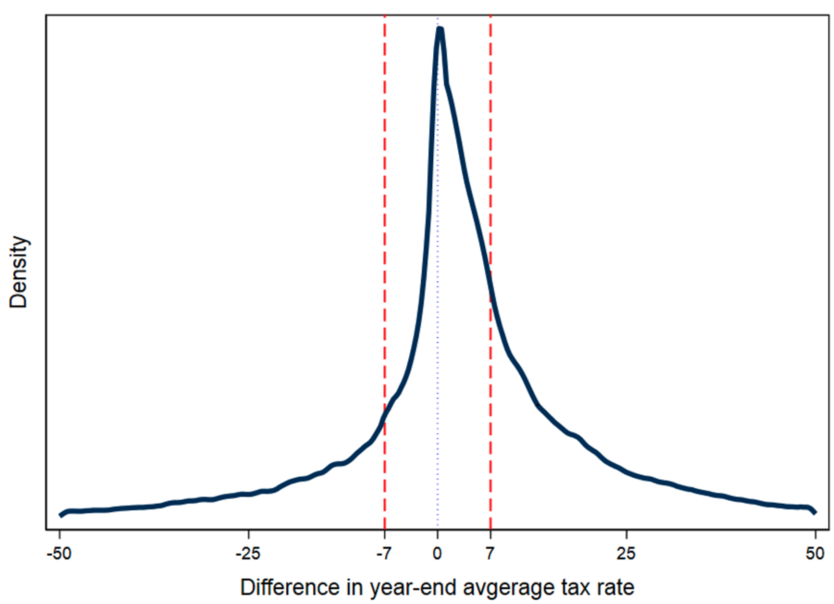

**Notes.** Figure 7 summarizes how average and marginal tax rates vary by household income and number of dependents for single and married filers enrolled in SNAP in California in 2016. I group tax units into bins of $2,000 in annual income by filing status and number of dependents, and within each bin, identify the mean marginal and average tax rate.

**Figure 8:** Distribution of cross-year differences in household income, average tax rate, and predicted $\omega$

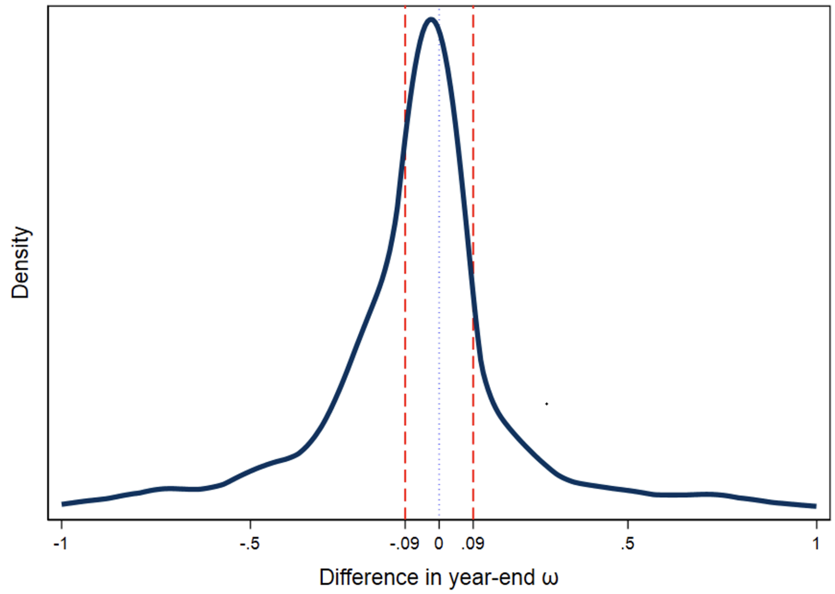
**(a)** Annual earnings



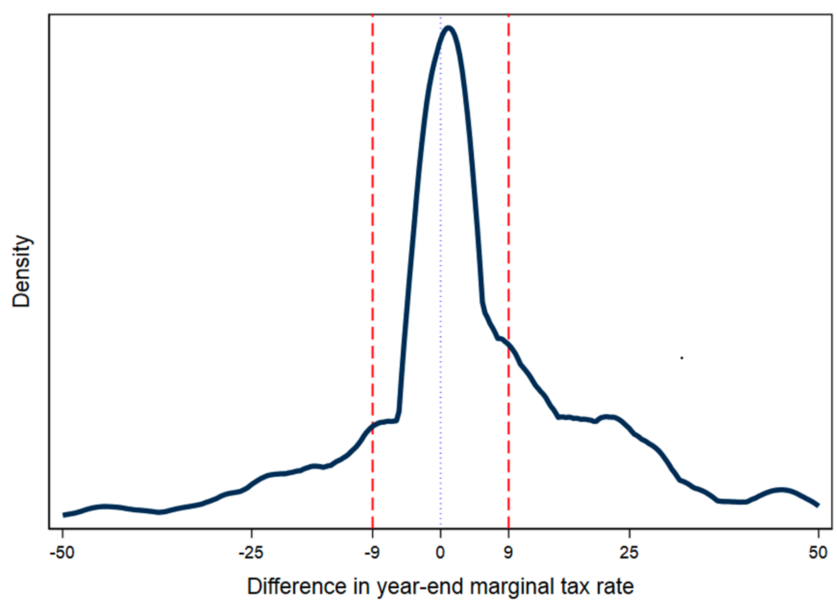

**(b)** Average tax rate



**(c)** Predicted final quarter net of tax wage rate

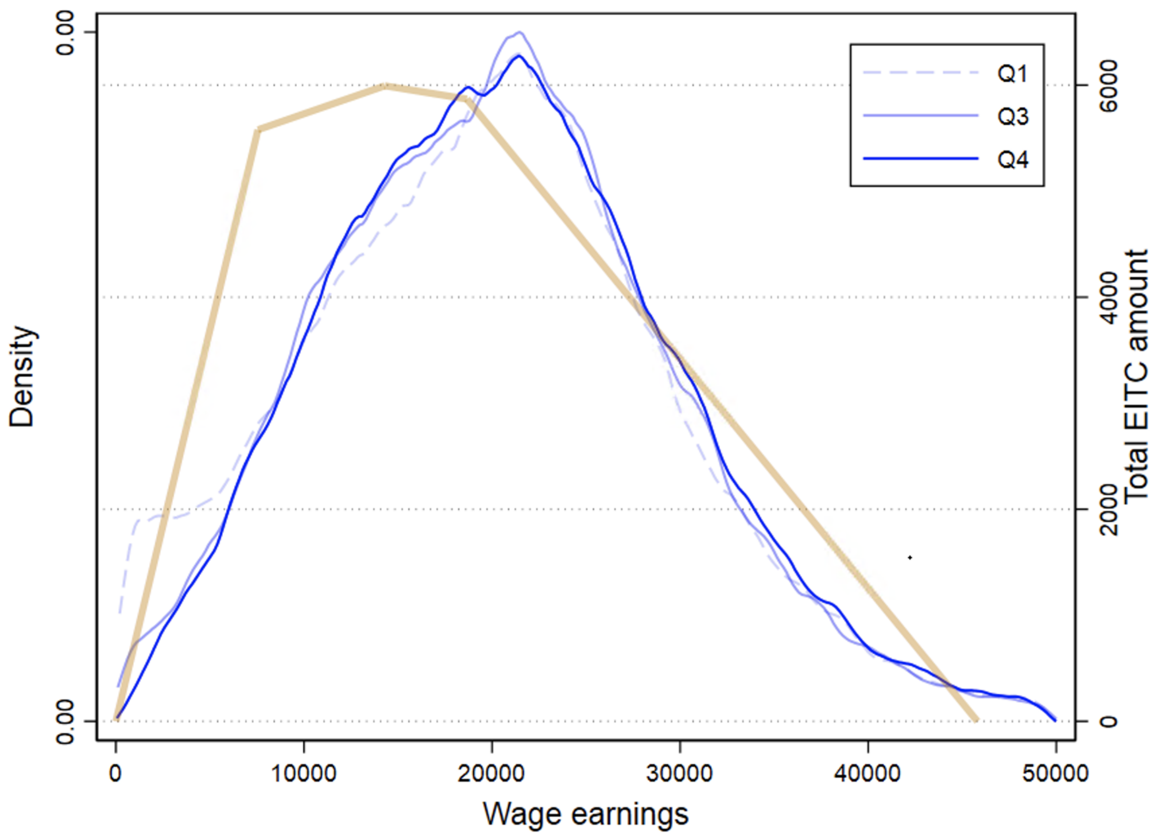



**(d)** Marginal tax rate



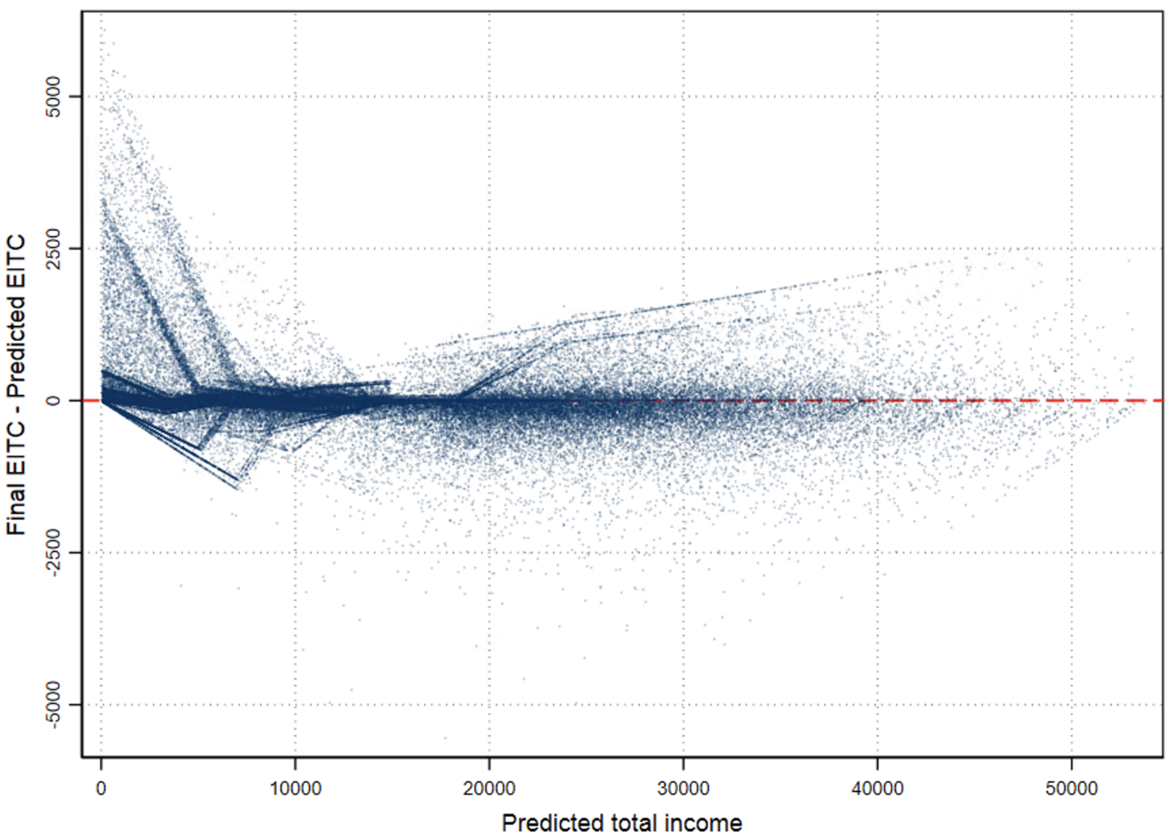

**Notes.** Figure 8 illustrates the differences in household income, average tax rate and $\omega$ across tax years within the same SNAP households. For all households, I subtract the value from the value from the previous tax year. I plot the kernel density of all these differences. For household income, I use a bandwidth of $100 and limit to differences within $25,000. For average tax rate, I use a bandwidth of half a percentage point and limit to differences within 50 percentage points. For predicted net of tax wage rate on fourth quarter earnings, I use a bandwidth of 5 percentage points and limit to differences within 75 percentage points. For the marginal tax rate, I use a bandwidth of 2.5 percentage points and limit to differences within 50 percentage points. The red dotted lines indicate the median absolute value difference, meaning half of households exhibit a difference between those bounds and the other half exhibit a difference outside those bounds.

**Figure 9:** Distribution of annual income and predicted annual income as of the end of the first quarter, SNAP households with two dependents, 2017




**Notes.** Figure 9 plots kernel density distributions of predicted annual wage earnings as of the end of the first quarter and third quarter, as well as the distribution of actual wage earnings, for SNAP households with two dependents in 2017. we use a bandwidth of $500 and limit to households with a maximum of $50,000. We overlay these distributions on the combined federal and state EITC schedule for a single filer with two dependents in 2017. From the first quarter to the last, the distribution of earnings shifts such that fewer households are located towards the beginning of the phase-in region and more are clustered at the top of the EITC range.

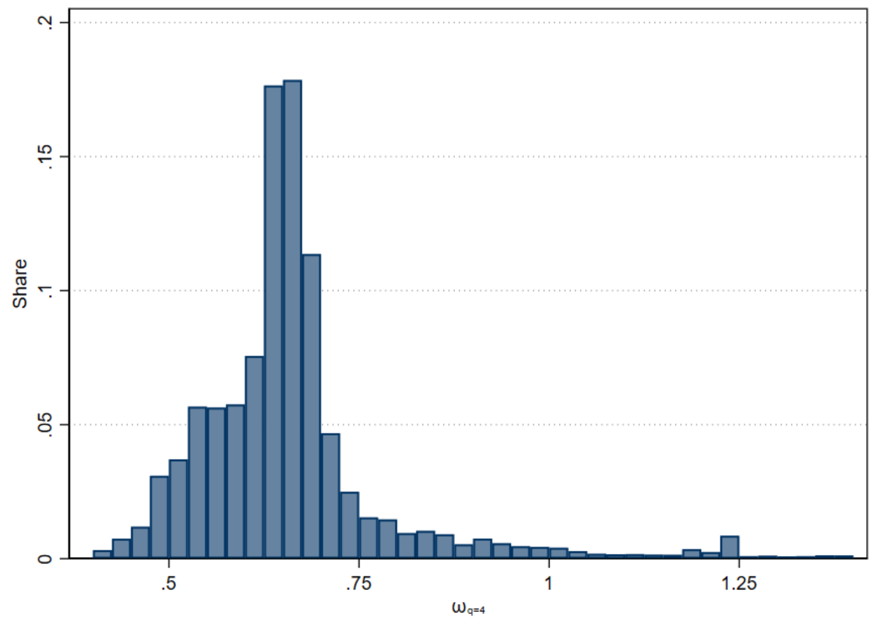
**Figure 10:** Predicted total EITC amounts versus final total EITC amounts, SNAP sample



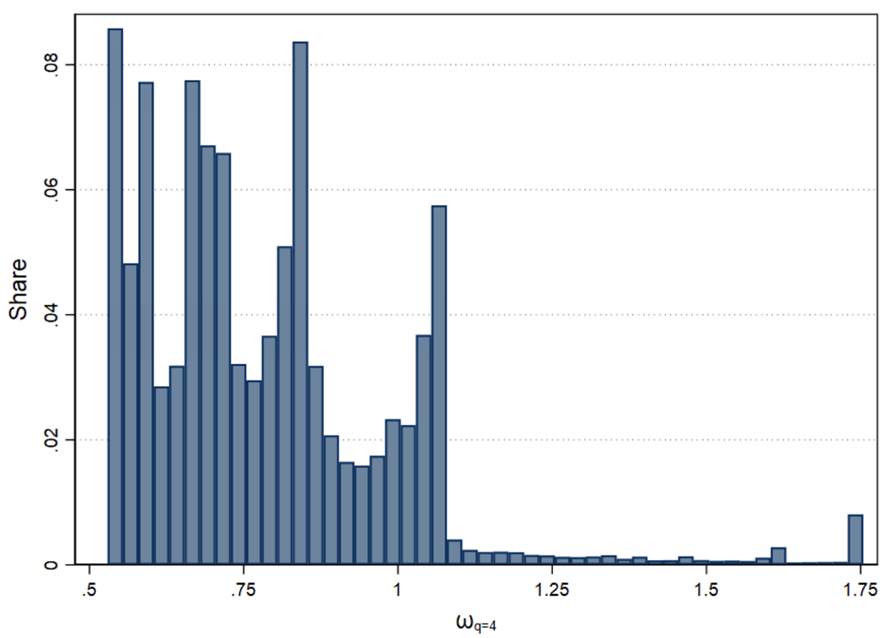

**Notes.** Figure 10 illustrates how those differences vary by predicted annual income. Each dot represents one SNAP households' predicted and actual EITC amount. We use a five percent sample of SNAP households in tax years 2015 to 2017

**Figure 11:** Distribution of $\omega$ in Q4 in the SIPP and SNAP samples

**(a)** SIPP sample



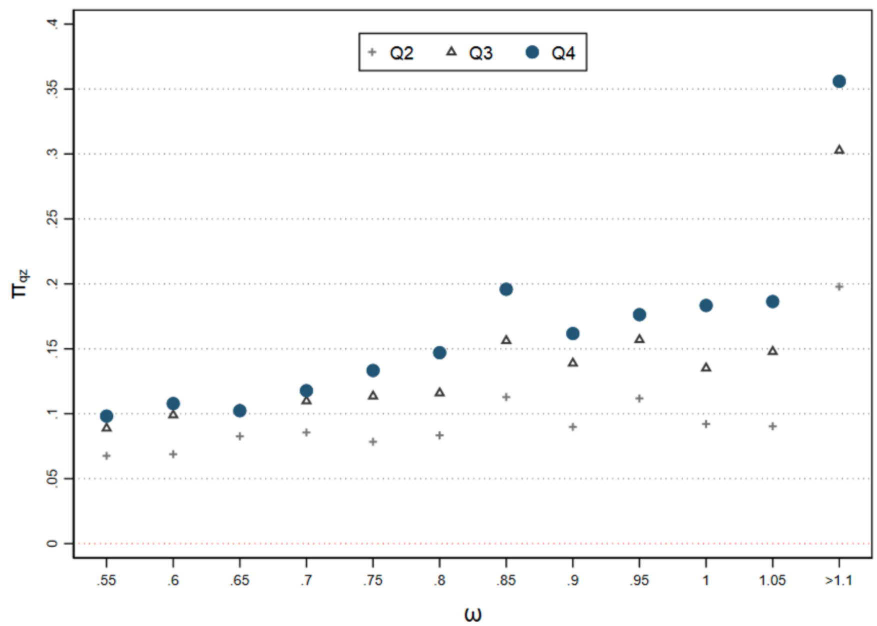

**(b)** SNAP sample



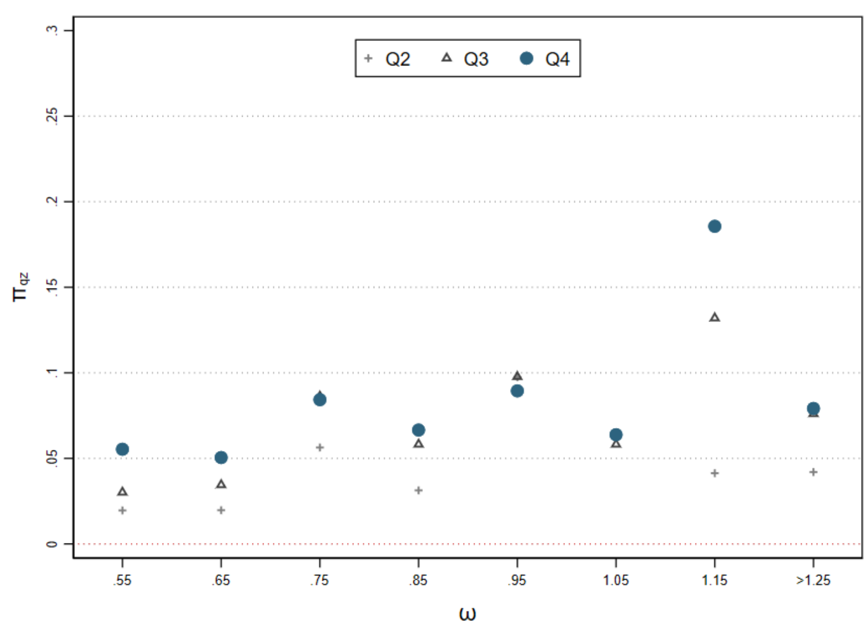

**Notes.** **??** illustrates the distribution of values of $\omega$, the predicted net of tax wage rate for subsequent quarter's earnings, for the fourth quarter in both the SIPP and SNAP sample.

**Figure 12:** Log earnings response to levels of predicted net of tax wage rate in subsequent quarter, SNAP households and tax units, 2015-2017

**(a)** SNAP sample



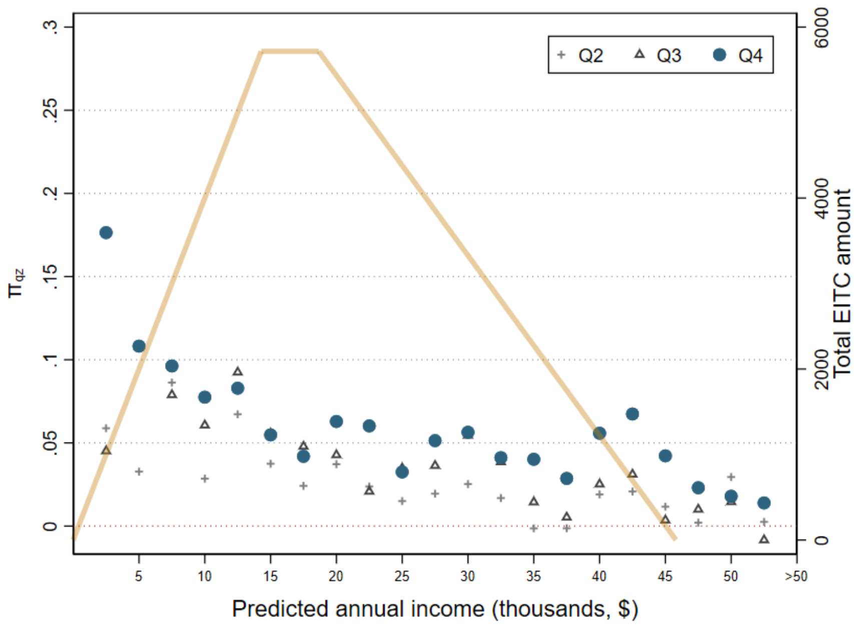

**(b)** SIPP sample



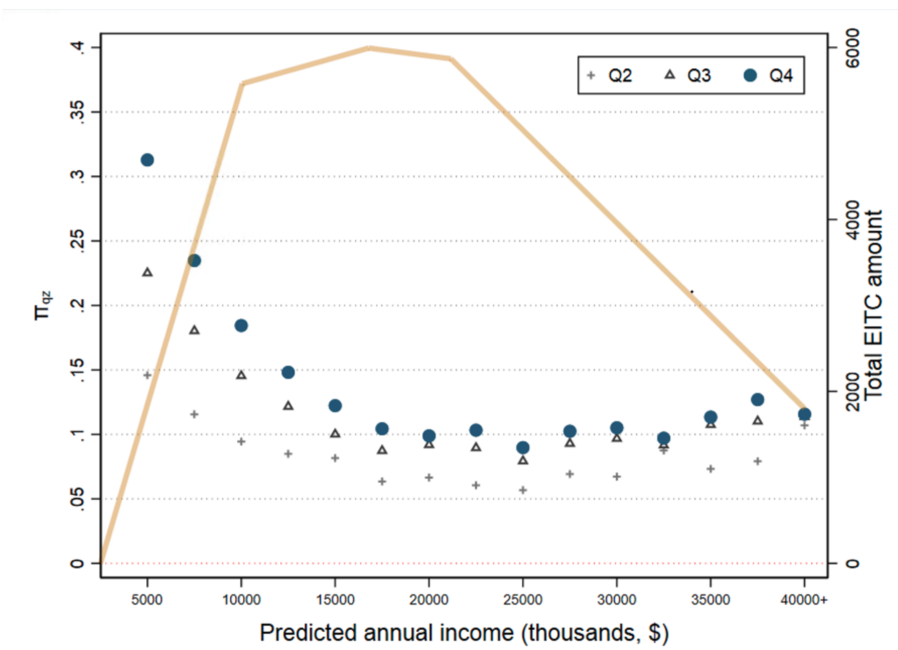

**Notes.** Figure 12 plots estimates of $\pi_{q\omega}$ from Eq 2. We bin households into twelve levels of $\omega$: below .55, above 1.1, and in between, groups of .05. We implement the same restrictions described above. We limit to households whose earnings in three previous quarters are between $2,000 and $75,000, and with positive earnings in all quarters in a tax year. We also restrict to households whose total EDD wages equal their state AGI. Standard errors are clustered at the household-level.

**Figure 13:** Difference in earnings adjustment between quarters 2, 3 and 4 relative to quarter 1 over predicted annual income

**(a)** SIPP sample




**(b)** SNAP households




**Notes.** Figure 13 plots estimates of $\pi_{qz}$ from Eq 3. The coefficients identify the difference in log earnings by predicted annual income between each calendar quarter relative to the first quarter. I overlay the estimates from the SIPP sample on the EITC schedule for a family with two dependents in 2008. I overlay the estimates among the SNAP households on the combined EITC schedule in California for a household with two dependents in 2017. Standard errors are clustered at the household-level.