Estimating Intensive and Extensive Tax Responsiveness: 
Do Older Workers Respond to Taxes?*

Abby Alpert†
David Powell‡

March 2016

Abstract

This paper studies the impact of income taxes on the labor supply decisions of older individuals. We jointly estimate intensive and extensive margin tax elasticities while addressing selection issues that have previously hindered consistent estimation of labor supply effects. We find large and statistically significant labor force participation tax elasticities for the population ages 62-74. We also estimate statistically significant effects on the intensive margin. Modeling two proposed age-targeted tax reforms, our estimates imply substantial scope for increasing labor force participation rates of older individuals through the tax code.

Keywords: Labor Supply Estimation, Retirement, Income Taxes, Sample Selection, Nonlinear Budget Sets
JEL Classification: H24, J20, J26

---

*We would like to thank Michael Dworsky, Jon Gruber, John Laitner, Nicole Maestas, Kathleen Mullen, Jim Poterba, Susann Rohwedder, Hui Shan, David Stapleton and conference and seminar participants at the Association for Public Policy Analysis and Management Fall Research Conference, Michigan Retirement Research Center Conference, National Tax Association Conference, RAND, and the Retirement Research Center Consortium for their helpful comments. We received especially insightful comments from our conference discussants Robert Carroll, David John, and David Richardson. We also thank Dan Feenberg for assistance with the NBER TAXSIM program. The research reported herein was performed pursuant to a grant from the U.S. Social Security Administration (Grant #RRC08098401-07)).

†University of California, Irvine, aalpert@uci.edu
‡RAND, dpowell@rand.org, 1776 Main St.; Santa Monica, CA 90407; 310-393-0411
1 Introduction

Economists and policymakers have long been interested in understanding the effects of economic incentives on the retirement decisions of older workers. Delaying retirement and extending working lives has important consequences for the financial viability of Social Security in the United States and the overall productivity of the economy (Maestas and Zissimopoulos (2010)), while also improving the welfare of older individuals as additional labor earnings supplement savings and Social Security benefits.\footnote{Butrica, Smith and Steuerle (2006) estimate that an additional year of work increases annual retirement income by 9%, with even larger returns for low-income individuals.} Due to the potential benefits of systematic delays in retirement, there are large literatures investigating the labor supply responses to Social Security benefits (see Feldstein and Liebman (2002) for a review), pensions (e.g., Samwick (1998); French and Jones (2012)), and Medicare (e.g., Blau and Gilleskie (2006); French and Jones (2011)). One policy that has been largely unexplored in the traditional retirement literature is the effect of income taxes on retirement decisions. Income taxes affect individuals’ incentives to work and, as such, the tax code is a potentially useful, but generally overlooked, policy lever to encourage individuals to earn more and remain in the labor force longer.

In general, the United States tax code treats older and younger individuals alike, with a few exceptions such as the age 65+ deduction and elimination of the Earned Income Tax Credit (EITC) at age 65. Some have suggested scope for more age-targeted tax policy (e.g., Kremer (2002)). Banks and Diamond (2010) in the Mirrlees Review recommend increasing the age dependence of taxes, calling the idea “a case of theory being ahead of policy, with research on tax design needed.” Meanwhile, some economists have recommended eliminating the payroll tax after certain ages or after Social Security receipt (Biggs (2012); Laitner and Silverman (2012)). Elimination of income taxes for seniors earning less than $50,000 was proposed by Barack Obama in the 2008 presidential election,\footnote{See http://change.gov/agenda/seniors_and_social_security_agenda/ (accessed December 19, 2014)} and President Obama proposed extending the childless EITC to age 67 in the 2014 State of the Union Address.\footnote{See https://www.whitehouse.gov/sites/default/files/docs/eitc_report.pdf (accessed May 19, 2015)} Furthermore, since age is an observable variable that likely proxies for different levels of productivity and attachment to the labor market, “tagging” by age may also improve redistributive taxation (Akerlof (1978)). A small literature has estimated calibrated life-cycle models and found welfare gains when taxes are age-dependent (e.g., Weinzierl (2011), Karabarbounis (2016)).
While there exists a large literature which estimates the effects of taxes on labor supply (summarized in Keane (2011)) and on taxable income (summarized in Saez, Slemrod and Giertz (2012)), these studies often explicitly exclude older individuals from the analysis or estimate aggregate effects combining all age groups. Consequently, there is almost no empirical evidence on the extent to which older individuals respond to taxes and estimates of labor supply elasticities derived from younger populations may not generalize to older individuals.\footnote{Differences in health status or productivity could affect the labor supply preferences of older individuals; older workers may be receiving a regular stream of unearned income from Social Security or pensions, making them behave more similarly to “secondary earners,” for whom taxes have been shown to have a larger effect (Saez, Slemrod and Giertz (2012)); or social norms may impact decisions to continue working (Behaghel and Blau (2012)).}

In this paper, we aim to fill this significant gap in both the retirement and tax literatures by providing some of the first estimates of the effects of income taxes on both the intensive margin (i.e., labor earnings) and extensive margin (i.e., working versus not working) labor supply decisions of older workers. We study the population ages 62 to 74 in the 2000 Census and 2001-2008 American Community Surveys (ACS) which provide detailed information on earnings and employment. Because tax rates and earnings are mechanically linked, we exploit exogenous variation in federal income tax rates originating from two major legislative tax schedule changes that occurred during this time period: the Economic Growth and Tax Relief Reconciliation Act of 2001 and the Jobs and Growth Tax Relief Reconciliation Act of 2003. These tax schedule changes lowered tax rates substantially for some income groups, while leaving other groups relatively unaffected. Building on methods introduced by Auten and Carroll (1999), Gruber and Saez (2002), and others, our approach uses a simulated instrumental variable strategy which takes advantage of these policy-driven tax rate changes and their heterogeneous effects on the population due to non-linearities in the tax schedule.

Given the importance of the labor force participation margin for older workers, our empirical approach pays special attention to estimating extensive labor supply decisions and we introduce a method to jointly estimate both intensive and extensive margin responses to taxes, allowing for non-random selection into working. Our method is new to the tax and labor supply literatures which have typically estimated the intensive or extensive margin in isolation, and should be useful more broadly.

Specifically, we contribute two key innovations to the approaches often used in the tax and labor literatures. First, we extend the Gruber and Saez (2002) empirical framework to
isolate behavioral responses to taxes on the extensive margin. The Gruber and Saez (2002) approach identifies only intensive margin effects. Consequently, we are the first, to our knowledge, to show that non-linear tax schedules and legislative tax schedule changes can be exploited to simultaneously identify both intensive and extensive margin effects, which are of particular importance for older workers. Gruber and Saez (2002) show that nonlinearities in the tax schedule provide separate variation in marginal tax rates and after-tax income, which identifies the intensive margin substitution and income effects, respectively. We add to this approach by recognizing that nonlinearities in the tax schedule can also be used to separately identify yet another important dimension: the tax-based incentives to participate in the labor force. By simultaneously using the independent variation in marginal tax rates, after-tax income, and after-tax non-labor income driven by tax policy changes, we are able to separately estimate substitution and income effects along the intensive margin, as well as extensive margin effects.

Second, we account for issues of selection and unobserved earnings for non-workers by jointly estimating the intensive and extensive margin equations. The two main issues we address are: 1) in the intensive margin equation, the estimated earnings effect is conditional on working, yet the decision to work may be endogenous to tax incentives, thus leading to biased estimates; and 2) in the extensive margin equation, the main explanatory variable of interest (after-tax income if the individual works) is not observed for non-workers and these values must be imputed. Typically, the labor and tax literatures have estimated intensive and extensive margin equations separately (i.e., either estimating the effect of taxes on earnings or taxes on labor force participation). We introduce a straightforward method which estimates these equations jointly. This approach shows how the selection and imputation issues that have plagued estimation of either equation independently can be resolved if these equations are estimated simultaneously.

Specifically, our approach uses policy-driven changes in the after-tax incentives to work as a selection instrument for the decision to work. After-tax non-labor income affects labor force participation, but does not – conditional on the marginal tax rate and after-tax income – independently affect intensive labor supply outcomes, making it an ideal selection instrument since it plausibly satisfies the exclusion restriction required to implement a sample selection model. This provides a method for obtaining consistent estimates of the intensive margin equation. Once we have consistent estimates of the intensive labor supply parameters, we then can use these parameters to predict individual labor earnings for everyone in the sample, even those who do not work. With these consistent predictions, it is possible to construct the
after-tax income variable for everyone in the sample (workers and non-workers) and estimate the extensive margin equation.

The elasticity of taxable income and labor literatures typically ignore selection concerns. As noted in the review of the labor literature by Keane (2011), “it is common to ignore selection on the grounds that the large majority of adult non-retired men do participate in the labor market...Whether selection is really innocuous is unclear, but this view is adopted in almost all papers on males that I review.” Studies of older workers are likely to be especially prone to selection bias. Furthermore, the literature on female labor supply, which typically focuses on the extensive margin, imputes earnings for non-workers, either assuming that workers and non-workers are the same conditional on covariates or using the presence of young children as a selection instrument for labor force participation. Given the known challenges in finding appropriate selection instruments for labor force participation, our approach should be useful more broadly in the labor literature.

We use our estimates of the tax elasticity of labor supply for older individuals to model two age-targeted policy experiments. First, we consider a policy which eliminates the employee portion of the Social Security payroll tax for older workers.\(^5\) The second policy expands the EITC, currently available to workers under age 65, to include older workers without dependents. A similar policy is discussed in Schimmel and Stapleton (2010) for older workers with health-related work limitations.\(^6\) These policies have the potential to substantially increase the incentives to work and delay retirement.

Our results suggest that taxes have a statistically significant and economically large impact on labor force participation and retirement decisions for older workers. On the extensive margin, we estimate large compensated participation elasticities. On the intensive margin, we estimate that individuals respond to the marginal net-of-tax rate, the amount that a worker keeps for an additional $1 in earnings. We estimate that a 10% increase in the marginal net-of-tax rate would increase labor earnings by 5% for women and 13% for men. Our estimates also strongly suggest that accounting for systematic selection into working is empirically important.

The elimination of the employee portion of Social Security payroll taxes for older workers is estimated to increase the percentage of both women and men working by 8.7 and

\(^5\)Social Security taxes can imperfectly be viewed as a forced savings mechanism for the prime-age working population. However, for older workers, it is almost a pure tax since individuals can only expect to receive a small share of what they pay into Social Security.

\(^6\)The EITC subsidizes labor earnings with a subsidy schedule that is non-linear in earnings. We model a policy which applies the most generous existing EITC schedule (households with three children) to the older population, irrespective of their number of dependents.
9.2 percentage points, respectively. Expanding the EITC to older ages would increase the percentage of women working by 9.2 percentage points. Men are not as responsive to the EITC since it targets a lower part of the earnings distribution. Overall, our estimates suggest substantial scope for impacting labor force participation decisions of older workers through the tax code.

In the next section, we further discuss how this paper is related to previous research in the tax and labor supply literatures. Section 3 describes the data and Section 4 includes the model and empirical strategy. We present our results in Section 5. Section 6 concludes.

2 Related Literature

This paper intersects with the literature on retirement and the literatures on the elasticity of taxable income and labor supply. Above, we noted the wealth of policies and incentives studied in the retirement literature. We contribute to this literature by studying a potentially important and understudied factor in retirement decisions – the tax code – which directly alters labor supply incentives.

A rich literature on the elasticity of taxable income (ETI) has used tax schedule changes to identify behavioral responses to taxes (e.g., Auten and Carroll (1999); Gruber and Saez (2002)) and a number of studies have found economically meaningful aggregate behavioral responses to tax policies during our study period (see Giertz (2007); Auten, Carroll and Gee (2008); Heim (2009); Singleton (2011); Saez, Slemrod and Giertz (2012)). However, the ETI literature has never focused on older individuals. Auten and Carroll (1999) limit their sample to ages 25-55, Feldstein (1995) excludes individuals over age 65, and the majority of the other studies estimate effects for an aggregate or younger population.

Our empirical approach builds on the methods introduced by Auten and Carroll (1999) and Gruber and Saez (2002) in the ETI literature which take advantage of the differential effects that the Tax Reform Act of 1986 (TRA86) and other legislative tax schedule changes had on households. In these papers, the authors instrument for the change in the marginal net-of-tax rate using its predicted change assuming that household real income stays constant from one period to the next. Thus, variation in the marginal net-of-tax rate originates from federal and/or state tax schedule changes. Due to the non-linear tax schedule, households experience different tax rate changes depending on their baseline income. Particular innovations of Gruber and Saez (2002) were to control flexibly for initial income due to concerns about mean reversion and the correlation between secular trends in income and tax rate changes. They also, notably, used tax schedule changes to separately identify the substitu-
tion and income effects so that the effect of the marginal net-of-tax rate can be interpreted as a compensated elasticity. We add to this literature by extending the Gruber and Saez (2002) approach to estimate the labor force participation margin of tax changes.

Another related literature has studied the effects of taxes and wages on labor supply, typically measured as hours worked or labor force participation. This literature, summarized in Hausman (1985a), Blundell and MaCurdy (1999), and Keane (2011), typically finds that women are very responsive to taxes and wages, while prime-aged men are not. In general, this literature also does not study older workers and frequently even eliminates them from the analysis. Many influential studies have selected on individuals by age, usually using a maximum cutoff of 50, 55, or 60.7

Given the importance of the labor force participation margin for our population, we further discuss the subset of papers in the tax and labor supply literatures which explicitly model extensive margin decisions as a function of the pecuniary return to working. One issue that has been noted in this literature is that the main explanatory variable of interest (i.e., wages or total earnings) is missing for those who do not work. The literature has addressed this issue in one of two ways. First, for individuals who are not working, this literature imputes wages or total earnings as if they had worked. It is typical in this literature to impute earnings by assuming that workers and non-workers are the same conditional on covariates (see Meyer and Rosenbaum (2001) and Blau and Kahn (2007)). Second, other studies use selection models to impute earnings for non-workers. The excluded variable identifying the selection equation is the number of children or presence of young children in Eissa and Hoynes (2004) and Eissa, Kleven and Kreiner (2008). We build on this framework, but improve on the identification of the selection equation using a new instrumental variable which is derived from nonlinearities in the tax schedule. This strategy offers credibly exogenous variation in the selection mechanism and has broader applicability than previous instruments.

One literature which specifically addresses labor supply effects of taxes for older workers is the literature studying the effects of the Social Security Annual Earnings Test (Friedberg (2000); Gruber and Orszag (2003); Song and Manchester (2007); Haider and Loughran (2008); Gelber, Jones and Sacks (2013)). Findings in this literature are mixed with some evidence that Social Security recipients are responsive to the Earnings Test on the margin of labor earnings. Given that the earnings test is not a pure tax since it returns the benefits in an actuarially fair manner, it is possible that individuals’ responsiveness to a pure tax may

---

7See, for example, Hausman (1985b); Blomquist and Hansson-Brusewitz (1990); Triest (1990); Eissa (1995); Blundell, Duncan and Meghir (1998); Ziliak and Kniesner (2005); Blomquist and Selin (2010) which are just a small subsample of these studies.
Most relevant to our study, Laitner and Silverman (2012) simulates the effects of eliminating the payroll tax for older ages and concludes that this policy would delay retirement by, on average, one year. This work estimates a life-cycle model using data on consumption, work-limiting disabilities, and labor supply. Gustman and Steinmeier (2013) also estimates a structural life-cycle model and finds small increases in full-time work at ages 65+ if the employee portion of the payroll tax were eliminated. Our paper takes a different approach than the existing literature on tax policy for older workers by using tax policy changes as a source of identification, thereby providing the first “quasi-experimental” evidence of the impact of taxes on the labor supply decisions of older individuals. There are tradeoffs to the two approaches. Our results may speak more to the immediate effects of tax policy changes, but may not capture the full long-term effects that arise when individuals are able to anticipate the age-specific tax reduction. On the other hand, while a structural life-cycle model explicitly considers the dynamic aspects of labor supply decisions in response to income taxes, that approach requires making assumptions regarding a household utility function, modeling disability trajectories, and imposing further assumptions. Instead, we follow the approach of a long-standing and influential tax literature which studies the observed behavioral changes resulting from legislative tax changes, extending it to address behavior at older ages, and introducing a method to use natural experiments to jointly estimate intensive and extensive margin responsiveness.

3 Data

We use the 2000 Census and the 2001-2008 American Community Surveys (ACS) for adults ages 62-74. These data sets contain a rich set of information including detailed demographics, income, and labor supply information. The sample size is also large which is important given that we are focusing on a narrow age-group and aim to independently identify three separate, but correlated, tax variables.\footnote{We also find similar results using the Health and Retirement Study (HRS) in a previous version of this paper. However, the Census and ACS combined have a much larger sample size, providing more precision. HRS results are available upon request.} The Census and the ACS provide equivalent variables (Ruggles et al. (2015)) and are often linked together (e.g., Coile and Levine (2010)). Since the income variables refer to the previous year, our sample spans 1999-2007. These years bookend the major tax policies that we study. This study period also has the advantage of preceding the Great Recession.
The detailed income variables of the Census and ACS are beneficial for generating tax variables. We use NBER’s TAXSIM program (Feenberg and Coutts (1993)) to derive tax rates, tax liability, and labor taxes for each individual based on their household income and family characteristics. We use federal and states taxes plus one-half of FICA taxes in our calculations of tax rates and tax liability.\footnote{TAXSIM includes the age 65 deduction when applicable but, otherwise, does not use age information when calculating household tax information. Consequently, TAXSIM will assign the EITC to individuals ages 65+. We obtain the TAXSIM calculations of the EITC and subtract these values for individuals age 65 or older.} Some sources of non-labor income (e.g., Social Security benefits) are taxed differently than labor income and thus should not be included in the determination of the marginal tax rate with respect to labor income. Since we focus on labor supply incentives, we define the marginal tax rate as the additional taxes for the next dollar of a person’s labor income. Our tax liability measures include tax liability from all income sources and account for the unique treatment of each type of income by the tax code, as captured by TAXSIM.\footnote{The Census and American Community Surveys do not include information on capital gains, but “most previous studies have also excluded capital gains from their analysis” (Gruber and Saez (2002)). Capital gains are also excluded in more recent tax research (e.g., Burns and Ziliak (2016)).}

The advantages and disadvantages of studying tax responsiveness in secondary data sources such as the Current Population Survey or the Census relative to administrative data are discussed thoroughly in Burns and Ziliak (2016). For example, information on many deductions is not collected in the Census and American Community Surveys. On the other hand, we have access to a richer set of demographic characteristics, which is beneficial for our identification strategy. We also observe households that would not appear in tax panel data because they have very little income.

We can also proxy for retirement using the employment status variable. We define “retired” in our data by two criteria: (1) no individual labor earnings and (2) self-declared as not in the labor force.\footnote{One caveat is that the survey asks respondents about their current self-reported labor force status, while the labor earning and tax variables all relate to the previous calendar year. We do not view this as a limitation for our analysis, however, given that we are using the “retirement” variable as a more permanent indicator of leaving the labor force. Observing retirement in the following year is consistent with that interpretation.} Consequently, we can study two dimensions of the extensive margin: “Not Working” if no labor earnings in the previous year; and “Retirement” if not in the labor force and no labor earnings in the previous year.

We present summary statistics for our data in Table 1. We observe low employment rates for this population: 27% for women and 40% for men. These low rates highlight the need to account for systematic selection into working when modeling intensive labor supply
decisions.

4 Model and Empirical Strategy

In this section we discuss a basic theoretical framework for modeling intensive and extensive labor supply responses to income taxes. Our approach studies the different mechanisms through which the tax schedule can impact labor supply. We use this model to derive our empirical specifications.

4.1 Theoretical Framework

We consider a basic static framework where an individual maximizes utility that is a function of consumption and labor. The budget constraint includes labor income, non-labor income (assumed exogenous in this model) and tax liability which is a function of both labor earnings and non-labor income. The utility function also includes a parameter related to the cost of working and is similar in spirit to the model found in Eissa, Kleven and Kreiner (2008). The individual solves the following maximization problem:

$$\max_{c,L} U(c, L) - 1(L > 0)q \quad \text{s.t.} \quad c = L + y^o - T[L + y^o]$$

where $c$ represents consumption, $L$ is labor earnings ($U_L < 0$), $y^o$ is non-labor income, and $y = L + y^o$ is total income. $T[y]$ is total tax liability given total income $y$ and is non-linear in $y$. $q$ represents a fixed cost of working. The fixed cost of working is equal to zero for those who do not work and we assume $q > 0$.

A. Intensive Margin

If we assume an interior solution, then the first-order conditions imply:

$$\frac{U_L}{U_c} = -(1 - \tau),$$

$$c = L + y^o - T[L + y^o].$$

where $\tau$ represents the marginal tax rate ($T' = \tau$). The insight from these equations is that changes in labor earnings (conditional on working) are a function of changes in $1 - \tau$ (the marginal net-of-tax rate) and changes in $L + y^o - T[L + y^o]$ (after-tax income). Labeling
after-tax income as $ATI$, the model states that labor earnings can be written as:

$$L = L(1 - \tau, ATI)$$  \hspace{1cm} (1)

Consequently, the tax schedule alters intensive labor supply in the following manner:

$$dL = -\frac{\partial L}{\partial (1-\tau)}d\tau + \frac{\partial L}{\partial ATI}dATI.$$  \hspace{1cm} (2)

Define $\zeta^I = \frac{1-\tau}{L} \frac{\partial L}{\partial (1-\tau)}$ and $\eta^I = \frac{ATI}{L} \frac{\partial L}{\partial ATI}$. The $I$ superscript is used to denote that these are intensive margin elasticities. $\zeta^I$ is the intensive margin substitution effect, which we interpret as a compensated elasticity, given that we are holding after-tax income constant. $\eta^I$ is the intensive margin income effect.\footnote{The model in Gruber and Saez (2002) begins with taxable income as a function of $1-\tau$ and virtual income but concludes with the same specification as equation (4) and interprets the parameters in the same manner that we do. While virtual income is often used in tax papers, our model suggests that it does not have an independent role on labor earnings after accounting for the marginal net-of-tax rate and after-tax income.} Substituting these terms into equation (2), we get

$$\frac{dL}{L} = -\zeta^I \frac{d\tau}{1-\tau} + \eta^I \frac{dATI}{ATI}.$$  \hspace{1cm} (3)

The corresponding regression specification is

$$\ln L = \alpha^I + \zeta^I \ln(1 - \tau) + \eta^I \ln[y - T(y)] + \epsilon^I$$  \hspace{1cm} (4)

Gruber and Saez (2002) note that the effect of the marginal net-of-tax rate (substitution effect) and the effect of after-tax income (income effect) can be separately identified empirically due to the non-linearities in the budget constraint. The budget constraint is non-linear because the tax schedule sets different marginal tax rates for distinct segments of total income. Changes in the marginal tax rate are the same for everyone on the same segment (i.e., tax bracket) of total income, but changes in after-tax income vary depending on a person’s distance from the kink in the budget constraint.

Figure 1 plots an illustrative case. For simplicity, we graph the nonlinear budget set created by a tax schedule with two tax brackets. After-tax income is an increasing, non-linear function of taxable income. We consider the case where the marginal tax rate in the top bracket is reduced between periods $t = 0$ and $t = 1$, while the tax rate in the lower tax bracket remains constant. This change in the tax schedule affects the after-tax income and thus the labor supply. The non-linearities in the budget constraint lead to different elasticities for changes in taxable income and after-tax income.
bracket remains constant. Person A is located in the lower tax bracket, while persons B and C are in the top tax bracket. Comparing A and B, it is clear that the tax schedule change reduces the marginal tax rate for person B, while leaving the marginal tax rate for person A unaffected. Comparing B and C, we observe that while both individuals experience the same change in the marginal tax rate, they experience different changes in after-tax income (labeled \( \Delta ATI \)). Thus, the marginal tax rate and after-tax income are separately identified due to the nonlinearities in the budget constraint.

**B. Extensive Margin**

Individuals may decide not to work and this decision is also related to the tax schedule. In the above equations, we can solve for interior solutions \( c^* \) and \( L^* \). Then, we can compare the utility from working to the utility from not working. Consider an individual that is indifferent between working and not working:

\[
U(L^* + y^o - T[L^* + y^o], L^*) - q = U(y^o - T[y^o], 0).
\]

For the extensive margin, the model tells us that the decision to work \( (W) \) is dependent on after-tax income, after-tax non-labor income \( (ATNI) \), and the individual’s labor earnings if they work (represented by \( L \)):

\[
W = W(ATI, ATNI, L)
\]

Changes in working status due to tax schedule changes can be decomposed into three variables:

\[
dW = \frac{\partial W}{\partial ATI} dATI + \frac{\partial W}{\partial ATNI} dATNI + \frac{\partial W}{\partial L} dL \tag{6}
\]

Define \( \zeta^E = \frac{ATI}{W} \frac{\partial W}{\partial ATI} \) and \( \eta^E = \frac{ATNI}{W} \frac{\partial W}{\partial ATNI} \). These are the extensive margin substitution effect and income effect elasticities, respectively. We interpret \( \zeta^E \) as a compensated elasticity given that we hold non-labor after-tax income constant. This term tells us how individuals react to additional after-tax income if they work, holding the after-tax income they would receive if they did not work constant (i.e., this term is the additional amount of after-tax income due to working). Finally, \( \omega^E = \frac{L}{W} \frac{\partial W}{\partial L} \), which relates the disutility of additional labor earnings to the probability of working. Following from the model, holding after-tax (labor and non-labor) income constant, additional pre-tax labor earnings reduces utility. Individuals
that must earn more in pre-tax labor earnings to make the same amount in after-tax income are less likely to work. Substituting these parameters into the above equation, we arrive at the following relationship:

\[
\frac{dW}{W} = \zeta^E \frac{dATI}{ATI} + \eta^E \frac{dATNI}{ATNI} + \omega^E \frac{dL}{L} \tag{7}
\]

From this equation, we derive our regression specification

\[
P(\text{Work} = 1) = F\{\phi^E + \beta^E \ln [L + y^o - T(L + y^o)] + \theta^E \ln [y^o - T(y^o)] + \rho^E \ln L + \epsilon^E\} \tag{8}
\]

This specification differs slightly from some papers in the tax literature that have studied the decision to work (e.g., Eissa and Hoynes (2004); Gelber and Mitchell (2011)), though it follows naturally from our model. Other studies have modeled the decision to work as a function of: \(\frac{L - (T(L + y^o) - T(y^o))}{y^o}\), which is the share of labor earnings that an individual keeps if they work. This variable is related to our specification, except that it combines all three of our variables into one term. Taking the log of this term produces a similar expression as found in equation (8): \(\ln [L + y^o - T(L + y^o) - (y^o - T(y^o))] - \ln L\). The main difference is that this measure takes the log of the difference in after-tax earnings from working versus not working, whereas we include the log of after-tax income and the log of after-tax non-labor income separately. This allows us to estimate the response to the proportional increase in after-tax income from working (i.e., allowing for different effects depending on whether the person has a small or large amount of unearned income), rather than the level increase and is consistent with the intensive margin equation which assumes behavioral responses to the log of after-tax income. Our use of a different specification will require us to scale our estimates in order to compare magnitudes across studies, as discussed further in Section 5.3. Furthermore, our specification includes the log of pre-tax labor earnings as a separate variable. In our context, converting \(\ln [L + y^o - T(L + y^o)]\) to a rate variable would require the assumption that \(\omega^E = -\zeta^E\), a restriction that is not implied by our derivation.

Nonlinearities in the tax schedule can also be used to separately identify the effects of the additional after-tax income earned due to working — after-tax labor income (ATLI)\(^{13}\) — from after-tax income and the marginal net-of-tax rate, as illustrated in Figure 2.

\(^{13}\)We define ATLI as the additional amount of after-tax income received due to working. Holding after-tax income fixed, changes in ATLI are perfectly and inversely related to changes in ATNI. Thus, when we discuss our selection instrument, it is equivalent to discuss identification of ATNI and identification of ATLI. An increase in ATLI is an additional incentive to work since it implies additional monetary gains to working in after-tax dollars. A decrease in ATNI, holding ATI constant, implies the equivalent incentive to work.
Consider two different people who initially have identical pre-tax total income (marked $C$, as in Figure 1) but different levels of non-labor (NL) income (e.g., spousal earnings). Non-labor income for person 1 and 2 are represented by $C_{1}^{NL}$ and $C_{2}^{NL}$, respectively. The additional after-tax income earned by person 1 due to working is represented by the vertical distance between $C_{1}^{NL}$ and $C$. Suppose the tax rate decreases for the top tax bracket between periods $t = 0$ and $t = 1$, as before. Note that after-tax labor income (labeled $\Delta ATLI_{C1}$ and $\Delta ATLI_{C2}$), the pecuniary incentive to work, have increased more for person 1 than for person 2 following the tax cut. Holding everything else constant, person 1 benefits from the tax cut only if she works. However, person 2 benefits from the tax cut regardless of whether or not she works, so the additional amount she earns due to the tax cut if she works relative to if she does not work is smaller. In other words, the benefits of working have increased for person 2 but have increased even more for person 1. Equivalently, the tax change increases after-tax non-labor income (i.e., ATNI) for person 2, but does not change after-tax non-labor income for person 1. This reduces the incentive to work for person 2 relative to person 1. Thus, differential changes in ATLI (or, equivalently, ATNI), holding the tax rate and ATI constant, result from variation in distance from the kink using only non-labor income.

Consequently, we can find two people who experience the same change in the marginal tax rate and after-tax income, but experience different changes in after-tax labor income (equivalently, different changes in ATNI) due to a legislative tax change. We take advantage of the separate identification of the marginal tax rate, after-tax income, and after-tax non-labor income to estimate the intensive and extensive margin effects of income taxes.

4.2 Empirical Strategy

Our empirical strategy models and estimates the impact of taxes on both the intensive and extensive margins of labor supply for older workers, using the insights of the above theoretical framework. We discuss the intensive margin first, followed by the extensive margin.

4.2.1 Intensive Margin Effect

We begin by modeling intensive labor supply decisions, measured as labor earnings. We use labor earnings as our primary outcome of interest because it is the product of a host of choices that may respond to tax incentives such as hours worked, amenity preferences, and effort. Labor earnings is thus a useful summary metric that combines all of these compo-
Given that the labor supply literature has consistently found that men and women respond to labor market incentives in different ways, we perform all analyses separately by gender.

Our specification models changes in labor earnings as a function of changes in the marginal net-of-tax rate (substitution effect) and changes in after-tax income (income effect). This equation is similar to the main specification used in the elasticity of taxable income literature:

$$\ln L_{it} = \alpha_t + X'_it\delta + \beta^I \ln(1 - \tau_{it}) + \theta^I \ln (y_{it} - T_t(y_{it})) + \epsilon_{it} \tag{9}$$

where $L$ is own-labor income, $\tau$ is the marginal tax rate, such that $\ln(1 - \tau_{it})$ represents the log of the marginal net-of-tax rate for person $i$ in period $t$. $y$ is total household income (including non-labor income) and $T(y)$ is total tax liability for income $y$. Then, $\ln (y_{it} - T_t(y_{it}))$ is the log of after-tax income. $X$ is a vector of covariates. These covariates are important because our identification strategy compares outcomes of individuals with the same covariates over time. Our covariates include indicators based on age group, race, education, and marital status. Because spouses may coordinate their labor force decisions, we also include indicators for spousal age groups, spousal race, and spousal education. The specification also includes year fixed effects.

We restrict estimation of equation (9) to individuals with positive labor earnings, which motivates our concerns about systematic selection (discussed in Section 4.3.2). The substitution and income effects are separately identified using legislative tax schedule changes so that $\beta^I$ can be interpreted as a compensated elasticity (Gruber and Saez (2002)). We expect this parameter to be positive.

---

14There are a few other reasons why labor earnings are of particular interest. First, we are specifically interested in the potential ramifications of policies that alter older individuals’ incentives to work and the subsequent impact on earnings as a means of supplementing or replacing Social Security benefits. Second, our model suggests that individuals respond to the additional income earned by participating in the labor force so we need to estimate labor earnings for each individual in our sample to construct this measure. Note also the relevance of studying labor earnings relative to total taxable income. The tax code can and does tax labor income in a different way than it taxes other income. For drawing policy implications, it is important to understand how labor income responds to taxes independent of other sources of income.

15We include indicators for age groups 62-63, 64-67, 68-71, and 72-74.

16Using the Census and ACS categories, we include indicators for white, black, and other.

17We categorize educational attainment into 4 groups: less than high school, high school graduate, some college, and college graduate.

18We use the same age groups as before, except that we also include indicators for spouses outside of the 62-74 range.

19The spousal variables are all equal to 0 for single individuals.
4.2.2 Extensive Margin Effect

We also estimate extensive margin effects. According to our theoretical model, an individual’s decision to work is a function of the amount of after-tax income that she would make if she worked, the amount of after-tax income she would make if she did not work, and the pre-tax labor earnings if she worked. We model the extensive margin following Section 4.1.B:

\[
P(\text{Work}_{it} = 1) = F(\phi t + X'_{it}\gamma + \beta^E \ln [L_{it} + y^o_{it} - T_t(L_{it} + y^o_{it})] + \theta^E \ln (y^o_{it} - T_t(y^o_{it})) + \rho^E \ln L_{it} + \nu_{it})
\]

(10)

where \(y^o_{it}\) is non-labor income. \(T(L + y^o)\) represents the total tax liability if the individual works and earns labor income \(L\). \(T(y^o)\) is the individual’s tax liability if they do not work. This specification models the probability of working in period \(t\) as a function of the income in after-tax dollars that the individual receives if she works, conditional on the income in after-tax dollars that the individual receives if she does not work. We interpret \(\beta^E\) as a compensated elasticity. We expect \(\beta^E\) to be positive for the probability of working. We expect \(\theta^E\) to be negative as increasing after-tax non-labor income provides a disincentive to work. The specification also includes the term \(\ln L_{it}\), which is derived from our model. Additional after-tax income for working should induce more people to work, but it is also important to account for the amount of pre-tax labor earnings that are needed to achieve a given level of after-tax income. For a fixed \(\ln [L_{it} + y^o_{it} - T_t(L_{it} + y^o_{it})]\), we would expect that a larger \(L\) would deter work. Thus, we expect \(\rho^E\) to be negative and interpret it as a proxy for the disutility of additional work, since higher \(L\) represents more hours and effort for a given level of after-tax income. \(L_{it}\) and, consequently, \(L_{it} + y^o_{it} - T_t(L_{it} + y^o_{it})\) are not observed for non-workers. We discuss how we address this missing data issue in the next section. We also estimate equation (10) with “retired” as the outcome variable (defined in Section 3).

4.3 Identification Challenges

Equations (9) and (10) pose a few identification challenges. First, changes in labor earnings mechanically increase tax rates and tax liabilities such that OLS will not provide consistent estimates of equation (9). Similarly, in equation (10), individuals with higher \(L\) (and consequently, higher tax liabilities) may be more likely to work for reasons unrelated to after-tax earnings. Second, we do not observe \(L\) for individuals who do not work, and \(L\) is important for constructing two of the variables in the extensive margin equation. Third,
we can only estimate the intensive margin equation (9) for a selected sample of individuals who participate in the labor force. In the sections that follow, we discuss how we address these endogeneity and selection issues.

4.3.1 Instruments

To address the mechanical relationship between earnings and taxes, we create a set of instruments to isolate plausibly exogenous variation in the tax variables. Our two structural equations (9) and (10) include three tax-related variables: the marginal net-of-tax rate, after-tax income, and after-tax non-labor income. These are all potentially endogenous since taxes are a function of labor income and labor force participation. We implement an instrumental variable strategy that exploits independent variation in these tax-related variables that is derived from legislative tax schedule changes.

Specifically, we take advantage of changes in federal tax policy during our study period that changed tax-based incentives for reasons unrelated to individual changes in labor supply. During our sample period, there were two key tax reforms: 1) the Economic Growth and Tax Relief Reconciliation Act (EGTRRA) of 2001, which reduced tax rates for nearly every tax bracket with especially large changes for those with low income; 2) the Jobs and Growth Tax Relief Reconciliation Act (JGTRRA) of 2003, which also reduced tax rates, primarily focusing on relatively higher income households. Figure 3 shows changes in the federal marginal tax rate across our study period. For married couples filing jointly, reductions in the marginal tax rate over this time period ranged from 0 to 46 percent, depending on the household’s adjusted gross income.

We employ a simulated instrumental variables strategy which exploits the differential effect that these tax policy changes had on households based on their observed characteristics. This strategy is motivated by the method found in Gruber and Saez (2002) but also shares similarities with other simulated instrumental variable strategies (Currie and Gruber (1996a,b)). Our implementation is similar to the approach used in Burns and Ziliak (2016).

Our instrumental variable strategy involves pooling all observations in our data and running these observations through TAXSIM to calculate the tax variables for each observation for each year from 1999 through 2007. We then estimate the relationship between the simulated tax variables and the covariates defined by $X$ in equations (9) and (10) in each year and predict values for each tax variable based only on covariates. Finally, each observation is assigned the predicted values based on their covariates and the year – these are the “simulated instruments.” Consequently, two individuals with the same covariates $X$ will
be assigned different values of the instrument only because they face different tax schedules due to legislative changes.

Specifically, our method for constructing the instruments can be summarized by the following steps. We discuss construction of the simulated log of the marginal net-of-tax rate.

The instruments for the other tax variables are generated using the same procedure.

1. Holding real income and household characteristics constant, we simulate the log of the marginal net-of-tax rate for every observation in the sample assuming that they were subject to the year $s$ tax code. For example, we take the entire sample and calculate the log of the marginal net-of-tax rate under the 1999 tax code. We represent this variable by $\ln(1 - \tau_{it}^{1999})$, where $\tau_{it}^s$ is the tax rate that person $i$ in year $t$ would have faced under the year $s$ tax schedule given the same real income and household characteristics. We implement this step for all years 1999-2007.

2. For each $s$ and using the full pooled sample, we regress $\ln(1 - \tau_{it}^s)$ on $X_{it}$, where $X_{it}$ is the same vector of covariates as in the intensive margin and extensive margin equations. Let $\delta_s$ represent the coefficients on $X_{it}$ for the regression for year $s$. These estimated coefficients parameterize the relationship between covariates and the predicted log of the marginal net-of-tax rate.

3. Using these coefficients, we predict the log of marginal net-of-tax rate for each observation in the sample in each year: i.e., $\hat{\ln}(1 - \tau_{it}^s) = X_{it}' \hat{\delta}_s$.

4. We assign the predicted log of marginal net-of-tax rate based on $t$. Observations in year $t$ are assigned $\ln(1 - \tau_{it}^t)$.

It should be emphasized that the sample and covariates are held constant across regressions in Step 2. Moreover, the inputs used to generate $\ln(1 - \tau_{it}^s)$ are identical across years with the slight caveat that we adjust all income measures for inflation to hold real income constant. Consequently, the only reason that $\ln(1 - \tau_{it}^s)$ varies for $s \neq s'$ is because the tax code has changed. As a result, $\hat{\delta}_s$ (and, consequently, our instruments) only varies from one year to another due to tax code changes.

Restricting the instruments to vary based only on covariates ($X_{it}$) allows us to account for the exact function that generated the instruments in our specifications. We control for $X_{it}$, accounting for the independent effects of household characteristics on labor supply changes, and we control for the tax policy changes (i.e., year fixed effects) in our extensive and intensive margin equations. Thus, identification originates solely from the interaction of $X_{it}$ and the tax policy changes. In contrast, the tax literature following Gruber and Saez (2002), predicts tax changes based on initial income and characteristics and changes in the
tax code. One concern with this approach is that the instruments, which are functions of initial income, may be correlated with mean reversion and income trends (Weber (2014); Burns and Ziliak (2016)). Predicting the instruments based on covariates alleviates these concerns and our approach should be less susceptible to biases resulting from mean reversion and secular trends. In our robustness tests, we also account for differential trends more explicitly and find little evidence that they are driving our results.

In the end, we construct three instruments using this method:

1. Predicted log of the marginal net-of-tax rate: $\widehat{\text{MTR}}_{it}$
2. Predicted log of after-tax income: $\widehat{\text{ATI}}_{it}$
3. Predicted log of after-tax non-labor income: $\widehat{\text{ATNI}}_{it}$

The first and second instruments will be used for identification of equation (9). The third instrument will be included as a determinant of selection into labor force participation in our selection equation, which we discuss below. All three instruments are used to identify the extensive margin equation.\(^{20}\) Given that our analysis is performed separately by gender, we generate all instruments separately by gender.

4.3.2 Selection

Our second identification challenge is that we do not observe labor earnings for individuals who do not work. The concerns that arise from this are two-fold. First, the intensive margin labor supply equation is estimated for a selected sample of individuals who work. This is problematic if, as the tax schedule becomes more generous, individuals with higher (psychic) costs to working enter the labor force. These individuals will likely work less on average and, consequently, we may associate generous tax schedules with lower labor earnings, biasing against the predicted response. Second, the extensive margin labor supply equation contains two variables which include the labor earnings that the individual would make if they worked. These labor earnings are unobserved for non-workers, the majority of the sample.

We address these two issues by jointly estimating the intensive and extensive margin labor supply equations. Combining the extensive and intensive margin equations is helpful for two reasons. First, the extensive margin equation provides a useful exclusion restriction to identify the selection mechanism in the intensive margin labor supply equation. To control for selection in the intensive margin equation, we need an instrument that affects

\(^{20}\)The extensive margin equation includes three endogenous variables. The use of $\widehat{\text{ATI}}_{it}$ and $\widehat{\text{ATNI}}_{it}$ as instruments to identify the extensive margin equation is straightforward. $\widehat{\text{MTR}}_{it}$ is also an appropriate instrument because it independently shocks $\ln L_{it}$. This independent variation is necessary to identify the equation.
labor force participation, but does not independently affect labor earnings conditional on participation. Fortunately, the extensive margin equation (equation (10)) includes a variable that is excluded from the intensive margin equation (equation (9)): after-tax non-labor income. Thus, we can use predicted after-tax non-labor income as an exogenous shock to employment. This is an ideal instrument for selection in the intensive margin equation since after-tax non-labor income affects labor force participation, but does not – conditional on the marginal net-of-tax rate and after-tax income – independently affect labor income. We find that this selection instrument has a strong relationship with labor force participation.

We use this selection instrument to estimate a probit model (Heckman (1979)) of labor force participation and condition on a flexible function of the estimated index in the intensive margin equation to adjust for selection. Additionally, in an alternative specification, we use a semi-parametric approach to correct for selection which does not assume normality of the error term. In this semi-parametric approach, selection into employment implies that:

$$E\left[\epsilon_{it}\mid \text{MTR}_{it}, \text{ATI}_{it}, \text{ATNI}_{it}, X_{it}, \alpha_{it}, \text{Work}_{it} = 1\right] = \lambda(W'_{it}\zeta)$$  \hspace{1cm} (11)

where $W$ includes our instruments for the intensive labor supply equation, the selection instrument, and all exogenous variables in equation (9). We do not assume any functional form for $\lambda(\cdot)$ and instead use a series approximation, as suggested in Newey (2009). We estimate the selection equation using the monotone rank estimator introduced in Cavanagh and Sherman (1998), which requires no distributional assumptions to obtain consistent estimates (up to scale). We include a 10-piece spline in our intensive margin equation.

Second, estimating the intensive and extensive equations together is useful because the intensive labor supply equation provides consistent predictions of labor earnings for non-workers and we can use these predictions to estimate the extensive margin labor supply equation. After we have estimated the intensive labor earnings equation (adjusting for selection), we predict earnings and calculate tax variables for each person in the sample, including those who do not have any labor earnings. We use these estimates to construct the otherwise unobserved labor earnings (and related tax variables) in the extensive margin equation.

To summarize, while the labor and tax literatures have typically estimated intensive margin or extensive margin equations in isolation, we show that there are significant advantages to joint estimation. First, the extensive margin equation can be used to solve selection issues inherent in the intensive margin labor supply equation. Second, the intensive margin equation provides a way to impute otherwise missing wages for non-workers in the extensive
4.4 Implementation

Our method for estimating the intensive and extensive margin labor supply equations proceeds in four steps. We describe the technical details in Appendix Section A. First, we estimate the selection equation and predict the selection adjustment term. Second, we estimate the intensive labor supply equation using 2SLS, conditioning on a flexible function of the selection adjustment term. Because the selection adjustment term is estimated, we bootstrap for inference which accounts for the inclusion of an estimated term in the intensive margin equation. Third, we use the parameter estimates from this equation to predict labor earnings for the entire sample including those who do not work. We also estimate tax liabilities and after-tax income given these labor earnings estimates. Fourth, we estimate the extensive margin equation using the estimated labor earnings and after-tax income variables derived from the intensive margin equation.

5 Results

Before discussing the regression results, we provide graphical evidence relating the tax incentives to work to the probability of working. We use our instruments for after-tax income and after-tax non-labor income to generate the additional log income that an individual receives from working: $\hat{\text{ATI}}_{it} - \hat{\text{ATNI}}_{it}$. We create “cells” based on the covariates included in our regression: age group, education, race, spousal age group, spousal education, spousal race, and gender. We calculate the change in the predicted tax incentives to work for each cell from 1999 to 2007. We then divide the cells into quartiles based on the change in the predicted tax-based incentives and graph this against the change in the fraction of individuals working in those cells over the same time period. Figure 4 shows this relationship. This approach mimics our empirical strategy, linking predicted changes in the tax-based incentives to work to changes in the probability of working. We find a positive monotonic relationship between our instruments, representing the incentives to work, and the fraction of individuals working.

Next, we present our regression results in the order that the equations are estimated: selection equation, intensive margin equation, and extensive margin equation. For the latter two equations, we include estimates with (1) no selection adjustment; (2) a selection adjustment method generated by a probit regression; (3) a semi-parametric selection adjustment method. In the extensive margin estimation, the type of selection adjustment refers to the
method used to impute earnings (and the corresponding tax variables).

5.1 Selection Adjustment

In Table 2, we present results for the selection equation separately for women and men. Column (1) shows the results from a probit regression estimating the probability of working as a function of the three tax instruments and covariates. The predicted log of after-tax non-labor income is excluded from the intensive margin equation, separately identifying the selection adjustment term. Column (2) presents semi-parametric estimates of the same selection equation using the monotone rank estimator. The monotone rank estimator estimates the index without any distributional assumptions. Since these latter estimates are only identified up to scale, we normalize all of the coefficients so that the sum of the square of all coefficients is equal to 1. To aid comparison between columns (1) and (2), we normalize the probit estimates in the same manner. Columns (3) and (4) show the analogous results for men. We estimate a negative coefficient on the excluded instrument. As we would expect, additional after-tax non-labor income decreases the probability of working. Conditional on after-tax non-labor income, after-tax income (if the individual works) increases the probability of working. We also estimate that the predicted log of the marginal net-of-tax rate decreases the probability of working. This estimate is consistent with the hypothesis that, conditional on after-tax income, the probability of work decreases with additional pre-tax labor earnings. The estimates for the excluded selection instrument are statistically significant regardless of the estimation procedure used and are of similar magnitude across specifications and gender.

For both women and men, we have identified a variable which predicts labor force participation and is theoretically excluded from the intensive labor supply equation. We use the predictions from these estimates in our intensive margin estimation to account for selection.\footnote{Technically, it is possible to identify purely off of distributional assumptions using the Heckman (1979) method and a probit regression. Even with an excluded variable, some of the identification will originate from distributional assumptions. The semi-parametric method that we employ, however, requires an excluded variable that predicts labor force participation.}

5.2 Intensive Margin

Due to the mechanical relationship between income and taxes, estimating our intensive margin equation requires the use of instrumental variables. Our instruments strongly predict the endogenous tax variables. We discuss the results for the first stage of our intensive margin
equation in Appendix Section B.

Table 3 presents the results from 2SLS estimation of the intensive labor supply equation. We interpret the coefficients on the marginal net-of-tax rate as compensated elasticities since we separately account for income effects. When no selection adjustment is made (Column (1)), we estimate an elasticity of -0.817 for women. This estimate is large, statistically significant from zero, and the opposite sign that is predicted by theory. We also estimate a positive income effect, which we also would not expect. When we account for selection in Column (2), the coefficient on the marginal net-of-tax rate variable changes to the expected sign. We estimate a positive effect of 0.622. The Column (2) estimate does impose distributional assumptions on the selection equation. When we relax this assumption in Column (3), we estimate a similar effect of 0.518. This estimate is statistically significant at the 10% level. Our income effect estimate remains positive, but we cannot reject that the income effect is statistically different from zero.

We find that the selection adjustment is important for men as well. We estimate elasticities of 0.498 without the selection adjustment and 0.103 and 1.263 with the probit and semi-parametric selection adjustments, respectively. We cannot reject that the income effect is equal to zero. The use of the semi-parametric selection adjustment is especially important for men. In Section 5.5, we test the sensitivity of this estimate further to the inclusion of a more flexible function of the semi-parametric selection adjustment term and find that the estimate is robust to the use of a more flexible function.

The point estimates are generally on the higher end of the range of estimates found in the elasticity of taxable income literature which does not select on older ages. For example, Giertz (2007) estimates elasticities of 0.26 and 0.40 (depending on the years of the sample), Auten, Carroll and Gee (2008) estimates an elasticity of 0.4, and Singleton (2011) estimates an elasticity of 0.2 to 0.3. We find that women and men are especially responsive to marginal tax rates at older ages relative to the previous literature.

5.3 Extensive Margin

After using the intensive margin equation to predict labor earnings for everyone in the sample, including individuals who do not work, we then calculate the additional taxes that the individual would pay had they worked. We calculate the log of after-tax income (conditional on working) for each individual. We also control for the log of after-tax non-labor income and the log of pre-tax labor income (conditional on working). These three variables are endogenous and we use all three tax instruments to identify the extensive
margin equation.

Table 4 presents the instrumental variable estimates for the extensive margin equation using 2SLS. We estimate large extensive margin effects for both women and men. In Column (1), using earnings predicted from the intensive margin equation without a selection adjustment, we estimate that a 1% increase in after-tax income – holding after-tax non-labor income constant – increases the probability of working by 0.5 percentage points. We also estimate a negative relationship between after-tax non-labor income and the probability of working, as we would expect. Finally, holding after-tax income constant, we estimate that higher pre-tax labor earnings reduce the probability of working. This estimate is also the expected sign and suggests that higher required effort to make a fixed amount of after-tax income deters work.

When we adjust for selection, the magnitudes of the estimates increase, as shown in Column (2) for the probit selection correction. The semi-parametric adjustment increases the magnitudes even further, as reported in Column (3). In Column (3), we estimate that a 1% increase in after-tax income (if the individual works) increases the probability of working by 1.8 percentage points for women. We also estimate that a 1% increase in after-tax non-labor income decreases the probability of working by 0.2 percentage points. Finally, a 1% increase in pre-tax labor income decreases the probability of working by one percentage point.

We observe similar patterns for men. The magnitudes of the coefficients on after-tax income and after-tax non-labor income increase in magnitude when we account for selection. The sign of the estimate for the pre-tax labor income variable is wrong-signed in Column (4) without the selection adjustment, but the sign becomes negative when selection adjustments are included. The Column (6) estimates imply that a 1% increase in after-tax income increases the probability of working by 1.4 percentage points for men. A 1% increase in after-tax non-labor increase decreases the probability of working by 0.1 percentage points. Finally, a 1% increase in pre-tax labor income decreases the probability of working by 0.3 percentage points.

Our implied elasticities with respect to after-tax income are large – 6.5 for women and 3.5 for men – due to the low labor force participation rates of these populations. These estimates are not directly comparable to the previous literature since we are estimating the labor force participation responsiveness with respect to after-tax income, whereas previous

\[ \frac{\beta E \times \frac{1}{P(work)}}{24} \]

\[ \text{Among individuals ages 62 to 74, the probability of working is 0.274 for women and 0.400 for men. We use these probabilities to construct elasticities from the estimates from Table 4. We calculate these elasticities using } \beta E \times \frac{1}{P(work)} \text{.} \]
studies typically estimate participation elasticities with respect to after-tax labor income, defined as labor earnings minus the additional taxes paid because of those labor earnings. Since a 1% increase in after-tax labor income would lead to a less-than-1% increase in after-tax income, we would expect to generate larger elasticity estimates than those found in the literature. In our data, a 1% increase in \( L - T(L + y^o) + T(y^o) \) is only 0.19 times as large as a 1% increase in \( L + y^o - T(L + y^o) \). Scaling our estimates by this factor provides elasticities of 1.2 for women and 0.7 for men, which are within the range of those found in the literature for the non-elderly.\(^{23}\) Eissa, Kleven and Kreiner (2008) summarizes the literature on the effects of taxes on non-elderly female household heads as finding a central value of 0.7 while Hotz and Scholz (2003) reports participation elasticities as large as 1.69.\(^{24}\) Overall, our results suggest meaningful scope for impacting labor force participation of older individuals through the tax code.

Finally, we repeat the above extensive margin analysis but focus on retirement as the outcome variable, where retirement is defined as having no labor earnings in the previous calendar year and self-reporting as not participating in the labor force in the current year. We use retirement as a measure of a more permanent labor force participation effect. These estimates are presented in Table 5. Focusing on the semi-parametric results (Columns (3) and (6)), we find that the estimates have similar magnitudes as the estimates for working, suggesting that the large increases in working due to after-tax income are almost entirely driven by reductions in retirement. This pattern of results is not surprising given that, for this age group, almost the entire population that is not working identifies as being out of the labor force. The results in Table 5, suggest that tax changes may have longer-term employment effects for the 62-74 population.

5.4 Policy Simulations

The key finding in our analysis is that labor force participation is highly responsive to taxes. In this section, we simulate the labor force participation ramifications of two policy experiments: 1) eliminating the employee portion of the payroll tax at age 65; 2) expanding the EITC to individuals ages 65 and over. We use the predicted probabilities from the

\(^{23}\)Our paper departs from the literature in several other ways, so one should exercise caution in extrapolating this scaling factor to our estimates. However, this provides a general sense for how large the discrepancy is due simply to the specification of the main extensive margin variable.

\(^{24}\)Hotz and Scholz (2003) summarize participation elasticities for women in the literature: 0.85 in Dickert, Houser and Scholz (1995), 1.16 in Eissa and Lieberman (1996), 0.96 in Keane and Moffitt (1998), 0.70 in Meyer and Rosenbaum (2001), 0.29 in Eissa and Hoynes (2004), and between 0.97 and 1.69 in Hotz, Mullin and Scholz (2010).
semi-parametric estimates (Table 4) and estimate the average change in the probability of working under these two tax policies. Since both of these policies increase the generosity of the tax code at specific ages, implementation of these polices may also have dynamic effects if we believe that individuals will shift their labor supply to periods in the life-cycle where they would earn more. We cannot study this possibility without imposing more restrictive assumptions. These estimates may be most relevant for understanding the short-term consequences of the introduction of these policies. The following estimates are likely lower bounds of the permanent effects if individuals would delay some of their labor supply until the period when they face lower taxes. We also do not quantify the corresponding labor supply reductions at younger ages.

In our first policy experiment, we consider the elimination of the employee portion of FICA taxes at age 65.\footnote{Laitner and Silverman (2012) eliminates both the employee and employer portions.} We assume that an equivalent lump sum tax is levied on each person such that we can ignore income effects.\footnote{We also hold pre-tax labor income constant.} For each person, we predict (1) the probability of working under the current tax rules in period $t$ and (2) the probability of working under the “counterfactual” tax rules (i.e., eliminating the employee portion of the payroll tax), substituting in:

$$\ln [L_{it} + y_{it}^o - T_{it}^c(L_{it} + y_{it}^o)],$$

where $T_{it}^c$ represents the counterfactual tax burden in period $t$ given the elimination of the employee portion of FICA taxes. The difference in these probabilities gives us the effect of this policy on labor supply behavior. Table 6 shows the results of this simulation.

In our baseline sample, 27.4\% of women and 40.0\% of men earn positive wages. Elimination of the employee FICA taxes would increase this percentage by 8.7 percentage points for women and 9.2 percentage points for men. We estimate nearly equivalent reductions in retirement. The results imply a 12\% reduction in the fraction of women not working and a 15\% reduction in the fraction of men not working. Laitner and Silverman (2012) finds that the elimination of the full payroll tax would, on average, extend working lives by one year. Our estimates imply smaller changes,\footnote{Even if we assume that the individuals incentivized to work in period $t$ work, on average, 2 years longer than they would have, we would still need to estimate much larger effects to predict an average increased working life of one year.} but these effects are still large and economically significant.

Our second policy experiment expands the EITC to the 65+ population while elimi-
nating the dependents requirement.\footnote{Following Schimmel and Stapleton (2010), we also allow the EITC subsidy to depend on individual earnings only, not total household earnings.} We implement this policy on our 65+ sample, again assuming that an equal lump sum tax is levied. We use the most generous EITC schedule in 2009, the first year with a new rate for individuals with 3 or more children and comparable to the current EITC schedule. In 2009, the credit was phased-in at a rate of 45% up to $12,570 of earned income for a maximum benefit of $5,657. The benefit remained constant between $12,570 to $16,450. The credit was phased out at a rate of 21.06%. Table 7 presents the results from this simulation. We estimate that this policy would increase the probability of working by 9.2 percentage points for women. The probability of working would increase by only 0.002 percentage points for men. This is due to the fact that working men are much more likely to be making too much to qualify for the EITC compared to women and those eligible would receive small payments. This estimate is statistically significant (because we predict large and precise increases in the probability of working for those affected by the policy) but is economically unimportant. The point estimates for the effect of the EITC expansion are larger for women than men, while estimates for the payroll tax reform are larger for men. Working women are more likely to be in the lower part of the earnings distribution which is better-targeted by the EITC expansion.

5.5 Robustness Checks

In this section, we study the robustness of our results. For each test, we repeat our entire four-step procedure and present the main results. We use the semi-parametric selection adjustment method as our preferred specification in all cases. The robustness results are reported in Table 8. The first row shows the intensive margin results for the coefficient on the marginal net-of-tax rate variable only (corresponding to Table 3). The second row presents the extensive margin estimates (corresponding to Table 4). The third row shows the results from the elimination of the employee portion of the payroll tax simulation and the final row shows the results from the EITC expansion simulation.

First, in columns 1 and 2 of Panel A, we repeat our main findings. Second, we conduct sensitivity tests of the functional form for the sample selection term in the intensive labor supply specification. In our main analysis, we used a 10-piece spline. In columns (3) and (4) of Table 8, we include a 20-piece spline. The results are similar, suggesting that our results are robust to more flexible functions of the selection adjustment term.

Third, we test for the importance of secular trends more explicitly in Columns (5) and
Our instrumental variable strategy uses the interaction of covariates and tax schedule changes for identification. As discussed in Section 4.3.1, this approach has advantages over the traditional Gruber and Saez (2002) approach because it should be more robust to mean reversion concerns and secular trends given that identification is not originating from individual-specific variation in initial income. As further validation of this strategy, we test explicitly for trends by controlling for measures of predicted labor earnings based on the covariates. We predict the log of labor earnings based on $X_{it}$ using the full sample, parallel to the creation of our instruments: $X_{it}^{'}\delta_L$. We interact this variable with year dummies and include these controls in our specifications. If differential trends are important, then we should observe that individuals with high predicted earnings experience different year-to-year earnings changes than those with low predicted labor earnings. These covariates should separately account for these trends. The results in Columns (5) and (6) suggest that trends are not confounding our estimates.

Fourth, in columns (7) and (8), we test for the possibility that part-time work transitions are affecting our estimates. It is possible that equation (9) does not fully encapsulate discrete intensive margin decisions such as the decision between full-time and part-time work. In principle, we could model this behavior explicitly.\footnote{This extension would require an additional equation and an equivalent instrument for the pecuniary incentives to work part-time (versus full-time).} Instead, we simply evaluate the possible effects of assuming that individuals respond to the marginal tax rate for intensive labor supply decisions. For working individuals that report usually working less than 35 hours per week, we calculate their hourly wages and then recalculate their labor earnings, assuming that they worked 35 hours per week. In other words, we make our entire working sample into full-time workers. Then we re-estimate our model. The results in Column (7) for women are similar to the main results. For men (Column (8)), the intensive margin results are also similar, suggesting that the intensive margin equation is not confounded by part-time work transitions. The extensive margin result for men is smaller, but the effects are still quite large overall.

### 6 Conclusion

This paper models both the intensive and extensive margins of labor supply, using each margin to enable more accurate and consistent estimation of the other. Both of these equations pose challenges for estimation even with appropriate instrumental variables due to possible selection bias and unobserved earnings. The extensive labor supply equation,
however, provides a natural exclusion restriction to account for selection in the intensive labor supply equation. This instrument is, to our knowledge, new to the labor supply literature, which has often noted that selection instruments meeting the required conditions are difficult to find. Moreover, the intensive labor supply equation provides a means of imputing a crucial variable in the extensive margin equation (earnings for individuals who do not work), allowing us to generate consistent estimates for that equation as well. This marks an improvement over the existing literature which has frequently imputed earnings without adjusting for selection, adopted selection instruments that are likely independently related to earnings, and used methods requiring strong distributional assumptions.

We find statistically significant and economically meaningful effects of taxes on labor force participation for older workers. These findings suggest scope for extending the working lives of older workers through the tax code. Since the prior labor supply and tax literatures rarely study the older segment of the population, this paper fills a large gap in these literatures and provides important estimates about the potential incentives in the tax code. We predict that age-specific tax reductions would cause this population to remain in the labor force longer and delay retirement.

Our estimates allow us to simulate the effects of two potential tax-based reforms. We find that the two policies would have significant effects on labor force participation. First, we estimate that eliminating the employee portion of the payroll tax would increase the percentage of women working by 8.7 percentage points and increase the percentage of men working by 9.2 percentage points. Second, we simulate effects of expanding EITC to older ages and estimate that this reform would increase the percentage of older female workers by 9.2 percentage points, with negligible effects for men. The methods introduced in this paper should be useful more broadly in the tax and labor supply literatures for estimating intensive and extensive labor supply responses.
References


Notes: This figure graphs after-tax income as a function of pre-tax income for a tax schedule with two brackets. The marginal tax rate for the top bracket decreases in period $t = 1$. Holding pre-tax income constant, persons A and B experience different changes in their marginal tax rates. Persons B and C experience the same change in marginal tax rates but different changes in after-tax income ($\Delta ATI$).
Figure 2: After-Tax Labor Income

Notes: This figure is the same as Figure 1 but with a focus on Person C. Person C with very little non-labor income ($C_{1}^{NL}$) experiences a large increase in the after-tax incentive to work ($\Delta ATLI$, after-tax labor income). Person C with more non-labor income ($C_{2}^{NL}$) experiences a smaller increase in the after-tax incentive to work. Both experience the same change in the marginal tax rate and after-tax income but different changes in after-tax labor income.
Figure 3: Federal Marginal Tax Rates, Pre- and Post-Tax Reforms

Notes: Marginal tax rates are for married couples filing jointly. Income is in constant 2013 dollars. Source: “U.S. Federal Individual Income Tax Rates History, 1862-2013 (Nominal and Inflation Adjusted Brackets),” Tax Foundation.
Figure 4: Change in the Probability of Working by Percentage Change in Predicted After-Tax Labor Income: 1999 to 2007

Notes: The y-axis is the change in the probability of working between 1999 and 2007 for each bin (i.e., the fraction working in 2007 minus the fraction working in 1999). The bins are defined by the change in the predicted log of after-tax income minus the predicted log of after-tax non-labor income (where these predictions are the instruments discussed in the text and entirely dependent on covariates). This is a measure of changes in tax-based incentives to work due to legislative policy changes only. We divide the sample into quartiles based on the magnitude of this change: Quartile 1 experiences the smallest increase and Quartile 4 experiences the largest increase. This approach mimics our empirical strategy. The y-axis is the change in the probability of working.
## Tables

<table>
<thead>
<tr>
<th>Demographics</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>67.7</td>
<td>67.5</td>
</tr>
<tr>
<td>Less than HS</td>
<td>24.3%</td>
<td>24.0%</td>
</tr>
<tr>
<td>HS Grad</td>
<td>37.5%</td>
<td>29.7%</td>
</tr>
<tr>
<td>Some College</td>
<td>22.4%</td>
<td>21.5%</td>
</tr>
<tr>
<td>College Grad</td>
<td>15.9%</td>
<td>24.9%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Labor Outcomes</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Personal Labor Earnings</td>
<td>$6,006.92</td>
<td>$16,758.83</td>
</tr>
<tr>
<td>Works</td>
<td>27.4%</td>
<td>40.0%</td>
</tr>
<tr>
<td>Retired</td>
<td>71.7%</td>
<td>58.9%</td>
</tr>
<tr>
<td>Total Household Income</td>
<td>$43,573.67</td>
<td>$56,503.59</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Tax Variables</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Marginal Tax Rate</td>
<td>20.9</td>
<td>24.0</td>
</tr>
<tr>
<td>N</td>
<td>1,647,003</td>
<td>1,415,300</td>
</tr>
</tbody>
</table>

Notes: All dollar values expressed in nominal dollars.
Table 2: Selection Equation

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>I(Work)</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Women</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Predicted ln(1 – Marginal Tax Rate)</td>
<td>-0.158***</td>
<td>-0.086***</td>
<td>0.017</td>
<td>-0.214***</td>
</tr>
<tr>
<td></td>
<td>[-0.218, -0.089]</td>
<td>[-0.093, -0.012]</td>
<td>[0.065, 0.079]</td>
<td>[-0.307, -0.171]</td>
</tr>
<tr>
<td>Predicted ln(After-Tax Income)</td>
<td>0.096***</td>
<td>0.096***</td>
<td>0.144***</td>
<td>0.112***</td>
</tr>
<tr>
<td></td>
<td>[0.079, 0.116]</td>
<td>[0.085, 0.135]</td>
<td>[0.120, 0.167]</td>
<td>[0.079, 0.145]</td>
</tr>
<tr>
<td>Predicted ln(After-Tax Non-Labor Income)</td>
<td>-0.046***</td>
<td>-0.039***</td>
<td>-0.044***</td>
<td>-0.049***</td>
</tr>
<tr>
<td></td>
<td>[-0.049, -0.044]</td>
<td>[-0.042, -0.035]</td>
<td>[-0.048, -0.041]</td>
<td>[-0.055, -0.041]</td>
</tr>
<tr>
<td>Probit</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Monotone Rank</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,647,003</td>
<td>1,647,003</td>
<td>1,415,300</td>
<td>1,415,300</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% confidence intervals in parentheses estimated using subsampling. Coefficients are scaled so that sum of the square of the coefficients is equal to 1. Other variables included: year dummies; age group fixed effects; education fixed effects; race fixed effects; spousal age group fixed effects; spousal education fixed effects; and spousal race fixed effects.

Table 3: Intensive Labor Supply Equation, 2SLS

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>ln(Labor Income)</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Women</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Selection Adjustment:</td>
<td>None</td>
<td>Probit</td>
<td>Semi-Parametric</td>
<td>Probit</td>
</tr>
<tr>
<td>ln(1-MTR)</td>
<td>-0.817***</td>
<td>0.622***</td>
<td>0.518*</td>
<td>0.498***</td>
</tr>
<tr>
<td></td>
<td>[-1.130, -0.502]</td>
<td>[0.235, 0.995]</td>
<td>[-0.023, 0.850]</td>
<td>[0.032, 1.001]</td>
</tr>
<tr>
<td>ln(After-Tax Income)</td>
<td>0.192***</td>
<td>0.195***</td>
<td>0.149</td>
<td>0.146***</td>
</tr>
<tr>
<td></td>
<td>[0.113, 0.319]</td>
<td>[0.103, 0.371]</td>
<td>[-0.040, 0.280]</td>
<td>[0.020, 0.254]</td>
</tr>
<tr>
<td>Observations</td>
<td>452,047</td>
<td>452,047</td>
<td>452,047</td>
<td>565,466</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% confidence intervals in parentheses estimated using subsampling. Other variables included: year dummies; age group fixed effects; education fixed effects; race fixed effects; spousal age group fixed effects; spousal education fixed effects; and spousal race fixed effects.
### Table 4: Extensive Labor Supply Equation (Working)

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Women</th>
<th>Men</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(After-Tax Income)</td>
<td>0.484***</td>
<td>0.931***</td>
</tr>
<tr>
<td>ln(After-Tax Non-Labor Income)</td>
<td>-0.078***</td>
<td>-0.139***</td>
</tr>
<tr>
<td>ln(Pre-Tax Labor Income)</td>
<td>-0.328***</td>
<td>-0.216***</td>
</tr>
<tr>
<td>Observations</td>
<td>1,647,003</td>
<td>1,647,003</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% confidence intervals in parentheses. Other variables included: year dummies; age group fixed effects; education fixed effects; race fixed effects; spousal age group fixed effects; spousal education fixed effects; and spousal race fixed effects.

### Table 5: Extensive Labor Supply Equation (Retirement)

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Women</th>
<th>Men</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(After-Tax Income)</td>
<td>-0.511***</td>
<td>-0.918***</td>
</tr>
<tr>
<td>ln(After-Tax Non-Labor Income)</td>
<td>0.080***</td>
<td>0.139***</td>
</tr>
<tr>
<td>ln(Pre-Tax Labor Income)</td>
<td>0.362***</td>
<td>0.366***</td>
</tr>
<tr>
<td>Observations</td>
<td>1,647,003</td>
<td>1,647,003</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% confidence intervals in parentheses. Other variables included: year dummies; age group fixed effects; education fixed effects; race fixed effects; spousal age group fixed effects; spousal education fixed effects; and spousal race fixed effects.

### Table 6: Effect of Eliminating Employee Portion of Payroll Tax

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>Working</th>
<th>Working</th>
<th>Retired</th>
<th>Retired</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effect of Age-Specific Payroll Tax</td>
<td>0.087***</td>
<td>0.092***</td>
<td>-0.086***</td>
<td>-0.092***</td>
</tr>
<tr>
<td>Baseline Rate</td>
<td>0.274</td>
<td>0.400</td>
<td>0.717</td>
<td>0.589</td>
</tr>
<tr>
<td>Sample</td>
<td>Women</td>
<td>Men</td>
<td>Women</td>
<td>Men</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. Uses results from Tables 4 and 5 to simulate effects of eliminating the employee portion of the payroll tax. We calculate after-tax labor income with and without the payroll tax, comparing the probabilities of not working and retiring. 95% Confidence Intervals in brackets.
Table 7: Effect of EITC Expansion

<table>
<thead>
<tr>
<th>Outcome:</th>
<th>Working</th>
<th>Working</th>
<th>Retired</th>
<th>Retired</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effect of Age-Specific EITC Expansion</td>
<td>0.092***</td>
<td>0.002***</td>
<td>-0.091***</td>
<td>-0.002***</td>
</tr>
<tr>
<td></td>
<td>[0.072, 0.112]</td>
<td>[0.002, 0.002]</td>
<td>[-0.111, -0.071]</td>
<td>[-0.002, -0.002]</td>
</tr>
<tr>
<td>Baseline Rate</td>
<td>0.274</td>
<td>0.400</td>
<td>0.717</td>
<td>0.589</td>
</tr>
<tr>
<td>Sample</td>
<td>Women</td>
<td>Men</td>
<td>Women</td>
<td>Men</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. Uses results from Tables 4 and 5 to simulate effects of extending the EITC to workers ages 65+. We calculate after-tax labor income with and without the EITC, comparing the probabilities of not working and retiring. 95% Confidence Intervals in brackets.
<table>
<thead>
<tr>
<th></th>
<th>Main Results</th>
<th>More Flexible Sample Selection Adjustment</th>
<th>Labor Earnings X Year Controls</th>
<th>Part-Time Adjustment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Women</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Men</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ ln(1-MTR)</td>
<td>0.518*</td>
<td>1.263***</td>
<td>0.627**</td>
<td>1.321***</td>
</tr>
<tr>
<td></td>
<td>[-0.023, 0.850]</td>
<td>[0.476, 2.306]</td>
<td>[0.028, 1.085]</td>
<td>[0.765, 2.414]</td>
</tr>
<tr>
<td>ln(After-Tax Labor Income)</td>
<td>1.776***</td>
<td>1.407***</td>
<td>1.841***</td>
<td>1.376***</td>
</tr>
<tr>
<td></td>
<td>[1.388, 2.165]</td>
<td>[1.220, 1.594]</td>
<td>[1.460, 2.221]</td>
<td>[1.194, 1.559]</td>
</tr>
<tr>
<td>Payroll Tax Simulation</td>
<td>0.087***</td>
<td>0.092***</td>
<td>0.091***</td>
<td>0.090***</td>
</tr>
<tr>
<td></td>
<td>[0.068, 0.106]</td>
<td>[0.080, 0.104]</td>
<td>[0.072, 0.110]</td>
<td>[0.078, 0.102]</td>
</tr>
<tr>
<td>EITC Simulation</td>
<td>0.092***</td>
<td>0.002***</td>
<td>0.092***</td>
<td>0.002***</td>
</tr>
<tr>
<td></td>
<td>[0.072, 0.112]</td>
<td>[0.002, 0.002]</td>
<td>[0.073, 0.111]</td>
<td>[0.002, 0.002]</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% Confidence intervals in brackets estimated in same manner as previous results. The first row presents estimates from the intensive margin equation. The second row includes estimates from the extensive margin equation. The third row presents estimates from the payroll tax simulation while the final row performs the EITC expansion simulation. All estimates refer to semi-parametric adjustment results.

Columns (1) and (2) repeat the main results presented in earlier tables.
Columns (3) and (4) includes a more flexible function of the selection term in the intensive margin equation.
Columns (5) and (6) interact predicted log of labor earnings with year fixed effects.
Columns (7) and (8) reassign the labor earnings of part-time workers to earnings if they made the same hourly wage but worked 35 hours per week.
Appendix

A Implementation Details

We explain the more technical details of the empirical strategy here. We describe each step in the order that it is estimated.

A.1 Step 1:

In the first step, we model the selection mechanism. When we report estimates that do not account for selection, this step is skipped. We must include all of the instruments used in the intensive labor supply equation. In the end, we estimate

\[ P(\text{Work}_{it} = 1) = F(\phi_t + X'_{it}\gamma + \beta_1\text{MTR}_{it} + \beta_2\text{ATI}_{it} + \beta_3\text{ATNI}_{it}), \eta \]  

(12)

The predictions provided by equation (12) are used as selection adjustments for the intensive equation. We do this in two different ways. First, we assume that \( F(\cdot) = \Phi(\cdot) \) and estimate equation (12) using a probit regression. This method is frequently used in the literature. However, instead of including an inverse Mills ratio (Heckman (1979)), we condition on a flexible function of the estimated index.

Second, we use a monotone rank estimator introduced in Cavanagh and Sherman (1998). This estimator does not estimate \( F(\cdot) \) but provides \( \sqrt{n} \)-consistent estimates up to scale of the coefficients in the argument of the function. We then predict the index function, which we denote as \( W_{it}'\hat{\zeta} \). The selection correction term is a function of this index and we follow the method of Newey (2009) by approximating this term with a spline using \( W_{it}'\hat{\zeta} \).\(^{30}\) The advantage of this approach is that the maximum rank estimator requires no distributional assumptions to obtain consistent estimates.

To implement the monotone rank estimator, we generate initial values through a probit regression and maximize the objective function using an MCMC optimization algorithm (see Chernozhukov and Hong (2003)). Confidence intervals are generated using a bootstrap.\(^{31}\)

\(^{30}\)Newey (2009) recommends the use of a spline over a power series.

A.2 Step 2:

The second step estimates the intensive labor supply equation. Because of selection, we estimate the following:

\[ \ln L_{it} = \alpha_t + X_{it}' \delta + \beta^I \ln(1 - \tau_{it}) + \theta^I \ln (y_{it} - T_t(y_{it})) + \epsilon_{it} \tag{13} \]

where \( \epsilon_{it} = \lambda(W_{it}' \zeta) + \mu_{it} \). In practice, we use a 10-piece spline in \( W_{it}' \hat{\zeta} \). We use \( \widehat{\text{MTR}}_{it} \) and \( \widehat{\text{ATI}}_{it} \) as instruments. We bootstrap Steps 1 and 2 jointly to account for the inclusion of an estimated term in equation (13).

We should highlight that 2SLS includes the selection adjustment terms in the first stage as well. This has practical importance in our strategy. Notice that for individuals not working, we do not observe their marginal net-of-tax rate if they had actually worked. We predict this variable from the first-stage regression in the same way that we will predict labor earnings.

We use 2SLS to obtain consistent estimates. Once we have consistent estimates for equation (13), we can predict \( L_{it} \) for our entire sample. This includes people who did not work. When using the Newey (2009) method, the constant term is not separately identified from the selection correction term. A method to estimate the constant term was introduced in Heckman (1990). Schafgans and Zinde-Walsh (2002) discuss consistency and asymptotically normality of this estimator. We implement this estimator to derive the constant term.

We predict earnings for the entire sample using the estimated coefficients in equation (13), the estimated constant term, and the imputed \( \ln(1 - \tau_{it}) \). In other words, we have consistent predictions of the tax variables and the coefficients to predict \( L_{it} \) for everyone in our sample. We use this to predict \( L_{it} \) using

\[ \hat{L}_{it} = \exp(\ln \hat{L}_{it}). \tag{14} \]

A.3 Step 3:

Once we have \( \hat{L}_{it} \), we can also calculate \( \hat{T}(y^o + \hat{L}) \) using NBER’s TAXSIM program. Then, we can construct the after-tax income measure assuming the individual works:

\[ \ln \left[ \hat{L}_{it} + y^o_{it} - \hat{T}_t(\hat{L}_{it} + y^o_{it}) \right] \]

44
A.4 Step 4:

Next, we estimate

\[ P(\text{Work}_{it} = 1) = F\left( \phi_t + X'_{it} \gamma + \beta^E \ln \left[ \tilde{L}_{it} + y_{it}^o - \tilde{T}_i(\tilde{L}_{it} + y_{it}^o) \right] + \theta^E \ln \left( y_{it}^o - \tilde{T}_i(y_{it}^o) \right) + \rho^E \ln \tilde{L}_{it} + \nu_{it} \right) \]

We estimate this equation using 2SLS.

B First Stage

Table B.1 presents the first stage results for the intensive labor supply equation. We present partial F-statistics, which measure the independent relationship of the instruments with each endogenous variable (Sanderson and Windmeijer (2015)). We find strong first-stage relationships for both women and men. The partial F-statistic for the marginal net-of-tax rate variable is 2493.45 for women and 642.18 for men. The partial F-statistic for the after-tax income variable is 1311.90 for women and 577.38 for men. The first-stage relationships are suitably strong by conventional cut-offs (Staiger and Stock (1997)).

Table B.1: Intensive Labor Supply Equation, First Stage

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>ln(1-MTR)</th>
<th>ln(After-Tax Income)</th>
<th>ln(1-MTR)</th>
<th>ln(After-Tax Income)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>0.578</strong>*</td>
<td><strong>0.308</strong>*</td>
<td><strong>0.396</strong>*</td>
<td><strong>0.664</strong>*</td>
</tr>
<tr>
<td></td>
<td>[0.548, 0.609]</td>
<td>[0.191, 0.425]</td>
<td>[0.368, 0.425]</td>
<td>[0.545, 0.783]</td>
</tr>
<tr>
<td>Predicted ln(1-MTR)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>0.035</strong>*</td>
<td><strong>0.494</strong></td>
<td><strong>0.037</strong>*</td>
<td><strong>0.405</strong>*</td>
</tr>
<tr>
<td></td>
<td>[0.028, 0.044]</td>
<td>[0.460, 0.528]</td>
<td>[0.030, 0.044]</td>
<td>[0.374, 0.435]</td>
</tr>
<tr>
<td>Predicted ln(After-Tax Income)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample</td>
<td>2493.45</td>
<td>1311.90</td>
<td>642.18</td>
<td>577.38</td>
</tr>
<tr>
<td>Women</td>
<td>452,047</td>
<td>452,047</td>
<td>565,466</td>
<td>565,466</td>
</tr>
<tr>
<td>Men</td>
<td>452,047</td>
<td>452,047</td>
<td>565,466</td>
<td>565,466</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% confidence intervals in parentheses estimated using heteroscedasticity-consistent standard errors. Other variables included: year dummies; age group fixed effects; education fixed effects; race fixed effects; spousal age group fixed effects; spousal education fixed effects; and spousal race fixed effects. Partial F-Statistics estimated using Sanderson and Windmeijer (2015).