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

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Abstract

This paper studies the impact of income taxes on the labor supply decisions of older workers, a population typically ignored in the tax literature. We jointly estimate intensive and extensive margin tax elasticities with a new method addressing selection issues that have previously hindered consistent estimation of labor supply effects. We find statistically significant and large labor force participation tax elasticities for this population. On the intensive margin, we do not find statistically significant effects. 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, Selection Models
JEL Classification: H24, J20, J26

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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 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.\(^1\) 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)), and the elimination of income taxes for seniors earning less

\(^1\)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.
than $50,000 was proposed by Barack Obama in the 2008 presidential election.\textsuperscript{2} 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 (2013)).

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.\textsuperscript{3}

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 use the 2000-2010 Health and Retirement Study (HRS) which provides the most detailed information available on earnings, employment, and retirement for a panel of individuals over the age of 50. 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

\textsuperscript{2}See http://change.gov/agenda/seniors_and_social_security_agenda/ (accessed December 19, 2014)
\textsuperscript{3}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)).
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. We simulate changes in tax rates for our sample
from one period to the next by applying the tax code in each period, holding real income
and household characteristics constant across periods. We use these predicted changes in
tax rates to instrument for actual changes in tax rates. Due to concerns of secular trends in
labor earnings across income groups (and mean reversion), we use predicted (based on co-
variates) labor earnings to generate our instruments so that no variation in the instruments
is originating from initial differences in labor earnings.

We contribute three key innovations to this approach. 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, commonly used in the existing
literature, 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, represented by after-tax labor income. By simultaneously using the inde-
pendent variation in marginal tax rates, after-tax income, and after-tax 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 labor income) 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 after-tax labor income as a selection instrument for the decision to work. We show that after-tax 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 labor income variable for everyone in the sample 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.” 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.

Third, the tax literature has noted the potential difficulties caused by differential income trends and mean reversion when exploiting income-based tax reforms for variation in tax rates. Our instrumental variable strategy addresses these concerns directly by generating instruments using predicted labor earnings and including the covariates used to predict labor earnings in all specifications. Consequently, no variation in the instruments (conditional on covariates) originates from initial differences in labor earnings.

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.\(^4\) 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.\(^5\) 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

\(^4\)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.

\(^5\)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.
impact on labor force participation and retirement decisions for older workers. On the extensive margin, the estimated compensated participation elasticity with respect to after-tax labor earnings is 0.99 for women and 1.20 for men. Studies in the literature have used the EITC to estimate labor force participation elasticities at younger ages, finding similar magnitudes. 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 Liebman (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). Additionally, we leverage the rich variables included in the HRS to study retirement and find evidence that tax changes may have permanent labor supply effects. In particular, we find statistically significant reductions in retirement for women when after-tax labor earnings increase.

On the intensive margin, we find little evidence that labor earnings for individuals ages 55-75 respond to the marginal net-of-tax rate, the amount that a worker keeps for an additional $1 in earnings. However, our intensive labor supply estimates have large confidence intervals, making it is difficult to rule out large elasticities.

Our policy simulations show that the elimination of the employee portion of Social Security payroll taxes for older workers is estimated to increase the percentage of both men and women remaining in the labor force by 9.0 and 7.4 percentage points, respectively. Expanding the EITC to older ages would increase the percentage of men not exiting the labor force by 8.0 percentage points, an 11% increase. For women, we estimate an increase in the probability of continuing to work of 9.8 percentage points, a 13% increase. Our estimates suggest substantial scope for affecting labor force participation decisions of older workers through the tax code.

In the next section, we 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 iden-
tify the substitution 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 60.6

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

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6See, 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.
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. Recent evidence (Gelber, Jones and Sacks (2013)) finds large behavioral responses. 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 be even larger.

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. While a structural life-cycle model explicitly considers the dynamic aspects of labor decisions in response to income taxes and complementarities with consumption, our approach does not require - for example - specifying a household utility function or modeling disability trajectories. Instead, we study the observed labor outcome changes resulting from legislative tax changes.
3 Data

We use the Health and Retirement Study (HRS) as our primary data source. The HRS is a panel data set of individuals ages 51 and over, containing a rich set of variables including detailed demographics, income, and labor supply information. The HRS interviews survey participants and their spouses every two years. We exploit the panel nature of the data in our empirical strategy by using period-to-period differences in outcomes to account for unobserved individual heterogeneity.

The highly detailed income variables of the HRS are crucial 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. The HRS income, asset, and demographic variables used as inputs to TAXSIM are taken from tax data files generated and published by RAND which produce cleaned and consistently defined variables beginning in 2000.\textsuperscript{7} We use federal taxes plus one-half of FICA taxes in our calculations of tax rates and tax liability.\textsuperscript{8}

We use the 2000-2010 waves of the HRS in our analysis for which we have consistently defined tax variables.\textsuperscript{9} The labor earnings, income, and derived tax variables refer to the previous calendar year so our final sample includes data from tax years 1999, 2001, 2003, 2005, 2007, and 2009.\textsuperscript{10}

\textsuperscript{7}See RAND Contributions at http://hrsonline.isr.umich.edu/ for tax files for 2000 and 2002; 2004-2010 tax files were obtained internally from RAND.

\textsuperscript{8}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.

\textsuperscript{9}Consistent tax variables are difficult to generate for the pre-2000 waves given changes in the HRS design. Also, the tax changes that occurred during the time period we study provide comparatively richer variation than the previous decade’s. The only tax change occurring between 1992 and 2000 was the Omnibus Reconciliation Act of 1993, which affected only those with at least $115,000 in annual income ($140,000 if married and filing jointly).

\textsuperscript{10}A small number of individuals were interviewed in the following calendar year and their annual income variables refer to 2000, 2002, 2004, 2006, 2008, or 2010. We exclude these observations from the analysis.
We restrict our sample to include everyone ages 55 to 75 who works in period $t$ linked to their outcomes in the following period. Given the structure of the data set, we use 2-year intervals in our specifications\textsuperscript{11} and refer to these years as periods $t$ and $t + 1$ to simplify notation throughout the paper. We exclude individuals not working in period $t$ from the sample since our empirical strategy relies on year-to-year differences in labor earnings, and we do not observe an initial measure of labor earnings for non-workers. It is possible to extend our method to account for individuals with zero earnings in period $t$, however this requires modeling the non-workers separately to study entry into the workforce. Given that entry into the labor force by non-workers is a relatively rare event for our older age group (only 6.5% of non-workers in period $t$ are working in the next period in our data), we do not have adequate power to study this group.

One advantage of the HRS is that we have detailed responses about employment status. We use this information to study two labor market outcomes: “not working” and retirement, which we construct as a special case of not working. We define “retired” in our data by two criteria: (1) no individual labor earnings and (2) self-declared as “retired.”\textsuperscript{12} Consequently, we can study two dimensions of the extensive margin: exiting the labor force (no labor earnings), which could be temporary or permanent; and retirement, where retirement is exiting the labor force plus declaring oneself retired.

We present summary statistics for our data in Table 1. While each person in our sample is working in period $t$, we observe a high probability of exit from employment in the following period. Only 72% of men and 73% of women working in period $t$ are working two

\textsuperscript{11}Gruber and Saez (2002), which primarily uses three-year intervals, finds little evidence that interval length changes their estimates in a meaningful manner. Powell and Shan (2012) also study the importance of interval length and find that once the interval is larger than one year, the estimates are largely consistent for all interval lengths. Though not shown, we have also used 4-year intervals and find consistent effects.

\textsuperscript{12}One caveat is that the survey asks respondents about their current self-reported retirement 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.
years later. 16% of the sample is retired by the next period.

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:

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

where $c$ represents consumption, $L$ is labor earnings ($U_L < 0$), $y^o$ is non-labor income, and $z = L + y^o$ is total income. $T[z]$ is total tax liability given total income $z$ and is non-linear in $z$. $q$ represents a fixed cost of working and enters the utility function. The fixed cost of working is equal to zero for those that 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) due to shifts in \(T[.]\). 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. 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 fixed preferences and $L^*$, we can see that labor force participation decisions are a function of the additional after-tax income if the person participates in the labor force, which includes pre-tax labor earnings ($L^*$), tax liability if the individuals works ($T[L^* + y^o]$), and the tax liability if the person does not work ($T[y^o]$). We use $L^* - (T[L^* + y^o] - T[y^o])$ as our measure of after-tax labor income.  

This result suggests that nonlinearities in the tax schedule can also be used to separately identify the effects of changes in after-tax labor income (the tax-based incentives to participate in the labor force) from after-tax income and the marginal net-of-tax rate, as illustrated in Figure 2. To illustrate, 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 $C_{1NL}$ and $C_{2NL}$, respectively. The additional after-tax income earned by person 1 due to working is represented by the vertical distance between $C_{1NL}$ and $C$. Suppose the tax rate decreases for the top tax bracket between periods $t = 0$ and $t = 1$, as before. Note that the pecuniary incentives to work (labeled $\Delta ATLIC_1$ and $\Delta ATLIC_2$) have increased more for

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13This measure is also most consistent with the literature, which has often used the net-of-average tax rate to model extensive margin decisions (e.g., Eissa and Hoynes (2004), Gelber and Mitchell (2011)). The net-of-average tax rate divides our measure by $L^*$. 

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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 doesn’t work is smaller. In other words, the benefits of working have increased for person 2 but have increased even more for person 1.

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. We take advantage of the separate identification of the marginal tax rate, after-tax income, and after-tax 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-
ents.\textsuperscript{14} 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:

\[ \ln L_{i,t+1} - \ln L_{it} = \alpha_t + X_{it}' \delta + \beta' [\ln(1 - \tau_{i,t+1}) - \ln(1 - \tau_{it})] \]

\[ + \theta [\ln (y_{it} - T_{t+1}(y_{it})) - \ln (y_{it} - T_{t}(y_{it}))] + \epsilon_{it} \]

where \( L \) is own-labor income, \( \tau \) is the marginal tax rate, such that \( \ln(1 - \tau_{i,t+1}) - \ln(1 - \tau_{it}) \) represents the change in the log of the marginal net-of-tax rate for person \( i \) between periods \( t \) and \( t + 1 \). \( y \) is total household income (including non-labor income) and \( T(y) \) is total tax liability for income \( y \). \( \ln (y_{it} - T_{t+1}(y_{it})) - \ln (y_{it} - T_{t}(y_{it})) \) is the change in the log of after-tax income due to tax burden shifts. We follow Powell and Shan (2012) when constructing the after-tax income variable, which is specified in a slightly different manner than the analogous term in Gruber and Saez (2002) (see Appendix Section A for more discussion). \( X \) is a vector of covariates. We create cells based on age and education of individual \( i \). There are 4 education categories (less than high school, high school graduate, some college, college graduate) and 5 age group categories (55-60, 61-64, 65-67, 68-70, 71+) for a total of 20

\textsuperscript{14}There 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, 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. Finally, 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.
cells. We include an indicator variable for each cell. Because spouses may coordinate their labor force decisions, we also include indicator variables based on spouse’s age (under 55, 55-60, 61-64, 65-67, 68-70, 71+). We also include indicators based on race/ethnicity.

Our specification includes year fixed effects. We also control for flexible functions in initial (period $t$) labor earnings. Our instrumental variable strategy (described below) relies on the inclusion of indicators based on initial labor earnings. We create 20 “bins” based on initial labor earnings and include dummy variables for each bin, as well as a 20-piece spline. We also include controls for the log of initial spousal earnings and the log of initial non-labor income.

We restrict estimation of equation (1) to individuals with observed labor earnings in both periods $t$ and $t+1$ (i.e., employed individuals), 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. We expect this parameter to be positive.

### 4.2.2 Extensive Margin Effect

We also estimate extensive margin effects separately for both the decisions to work and to retire. According to our theoretical model, an individual’s decision to work is a function of their additional after-tax labor income from working. We study the decision to work (or retire) in period $t+1$ for all individuals working in period $t$. We model the extensive margin in the following manner:

\[
P(\text{Work}_{i,t+1} = 1) = F\left(\phi_t + X'_it \gamma + \beta E\left\{\ln \left[ L_{i,t+1} - T_{i,t+1}(L_{i,t+1} + y_{i,t+1}^o) + T_{i+1}(y_{i,t+1}^o)\right]\right\} + \theta E\left\{\ln \left( y_{it} - T_{i+1}(y_{it})\right)\right\} + \nu_{it}\right)
\]

$^{15}$The results are not meaningfully affected by the use of different age categorizations.
where \( y_{o,t+1} \) 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 \( t + 1 \) as a function of the additional income in after-tax dollars that the individual receives if she works. We also include the log of after-tax income so that we can interpret \( \beta^E \) as a compensated elasticity. We expect \( \beta^E \) to be positive for the probability of working and negative for the probability of retiring (defined in Section 3). As before, construction of our income effect variables is discussed further in Appendix Section A. Note that \( L_{i,t+1} \) and, consequently, \( T_{t+1}(L_{i,t+1} + y_{o,i,t+1}) \) are not observed for non-workers in period \( t + 1 \). We discuss how we address this issue of missing data in the next section.

### 4.3 Identification Challenges

Equations (1) and (2) 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 (1). Similarly, in equation (2), 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 \( L_{i,t+1} \) for individuals who do not work in period \( t + 1 \). Thus, we do not observe \( \ln(L_{i,t+1} - T_{t+1}(L_{i,t+1} + y_{o,i,t+1}) + T_{t+1}(L_{i,t+1})) \) in equation (2) for the extensive margin. Third, we can only estimate the intensive margin equation (1) 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 (1) and (2) include three tax-related variables: the marginal net-of-tax rate, after-tax income, and after-tax 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. We also observe tax rate changes in 2009 due to changes to the EITC (which affect a small part of our sample) and the Making Work Pay Tax Credit which reduced marginal tax rates by 6.2 percentage points at low levels of labor earnings. 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 an instrumental variables strategy motivated by the approach found in Gruber and Saez (2002). These instruments have become standard in the tax literature. This approach involves two steps: first, calculate the marginal tax rate and tax liability for each person in period $t$ based on household income, assets, and other characteristics; second, holding real income and all other variables constant, calculate the individual tax rate and tax liability in period $t + 1$ applying the next period’s tax schedule. These calculations provide the predicted change in the log of the marginal net-of-tax rate and the predicted change in the log of after-tax income which are used as instruments for the actual changes in each variable. The Gruber and Saez (2002) predicted change in the log of the marginal net-of-tax
rate can be represented by

\[ \ln[1 - \tilde{\tau}_{t+1}(L_t, y_t^o)] - \ln[1 - \tau_t(L_t, y_t^o)] \]

where \( \tau_t(L_t, y_t^o) \) represents the marginal tax rate given labor income \( L_t \) and non-labor income \( y_t^o \).

Although the legislative tax schedule changes themselves are unrelated to changes in labor supply behavior, one concern with this approach is that variation in the instruments is inherently related to cross-sectional variation in initial income, which may itself predict changes in labor outcomes due to secular trends or mean reversion. To address this concern, papers in the literature control for initial income, typically employing a flexible spline.\(^{16}\)

We modify the standard approach to pay special attention to the potential biases arising from mean reversion and secular trends, employing a strategy similar to the one used in Gelber and Mitchell (2011) which predicts initial earnings based on covariates and applies the tax schedule to the predicted earnings. Our covariates include indicators based on period \( t \) labor earnings so we predict initial labor earnings based on these dummy variables.\(^{17}\) In other words, instead of using each observation’s actual initial labor earnings, we regress to the mean for each “bin” and then include indicators for each bin in all specifications. This approach eliminates any variation in the instruments originating from differences in initial labor earnings that are not independently and non-parametrically accounted for by the inclusion of the indicators in all of our specifications. We shut down variation (conditional on covariates) originating from differences in initial labor earnings. Consequently, we only use predicted labor earnings (\( \hat{L} \)) to generate our instruments for the marginal net-of-tax

\(^{16}\)Gruber and Saez (2002) uses a 10-piece spline in initial taxable income.

\(^{17}\)We could also use other control variables in making these predictions, but there is little gain in doing so given that the bins are already directly related to labor earnings. Given that our analysis is performed separately by gender, all predictions to generate the instruments are also performed separately by gender.
rate:

$$\ln[1 - \hat{\tau}_{t+1}(\hat{L}_t, y_{t}^o)] - \ln[1 - \tau_t(\hat{L}_t, y_{t}^o)]$$

The above instrument varies (conditionally) due to differences in initial non-labor income and tax schedule changes. We estimate the intensive margin equation in differences to account for the independent impacts of non-labor earnings on labor supply decisions.\(^{18}\) We generate the predicted change in the log of after-tax income variable in the same manner.

For the extensive margin equation, we estimate the effect of after-tax labor earnings on the probability of working. To generate the instruments for this equation, we predict both labor earnings ($\hat{L}_{t+1}$) and non-labor income ($\hat{y}_{t+1}^o$) based on covariates that we include in all specifications. Consequently, variation originates solely from tax schedule changes\(^{19}\) and our instrument can be presented by:

$$\ln[\hat{L}_{t+1} - T_{t+1}(\hat{L}_{t+1}, \hat{y}_{t+1}^o) + T_{t+1}(0, \hat{y}_{t+1}^o)].$$

We follow this same procedure to generate predicted after-tax income. In the end, we construct four instruments: predicted change in log of the marginal net-of-tax rate ($\hat{\Delta MTR}_{it}$), predicted change in log of after-tax income ($\hat{\Delta ATI}_{it}$), predicted log of after-tax labor income ($\hat{ATLI}_{it}$), and predicted log of after-tax income ($\hat{ATI}_{it}$). The first and second instruments will be used for identification of equation (1). The third and fourth instruments will be used

\(^{18}\)We will also test whether initial non-labor income predicts changes in labor supply behavior. We find no evidence that differential trends based on non-labor income are driving our results.

\(^{19}\)The implicit experiment is to compare two people with the exact same $X$ but under different tax schedules. We control for the independent effects of the covariates and the independent effects of the tax schedule (through the inclusion of year fixed effects). To the extent that the instrument varies based on initial labor earnings or other initial characteristics, this exact function is accounted for in all specifications and, consequently, the independent effects of these initial characteristics are controlled for. Identification comes from the interaction of tax schedule changes and their differential impacts on people based on initial characteristics. Consequently, the instrument is not simply associating people with different non-labor income to different labor force participation rates. Instead, it is comparing people with similar predicted labor and non-labor income under different tax schedules, controlling for the independent effects of the covariates used to predict income.
for identification of equation (2). Furthermore, the third instrument will be used as the selection instrument for labor force participation in our selection equation, which we discuss below.

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 in consecutive periods. 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, in the extensive margin labor supply equation, we are unable to observe the after-tax labor income measure – the main explanatory variable of interest – for those who do not work in period $t + 1$.

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 labor force participation, but does not independently affect labor earnings conditional on participation. Fortunately, the extensive margin equation (equation (2)) includes a variable that is excluded from the intensive margin equation (equation (1)): after-tax labor earnings. Thus, we can use predicted after-tax labor earnings as an exogenous shock to employment. This is an ideal instrument for selection in the intensive margin equation since after-tax 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 of labor force participation and construct the inverse Mills ratio following the standard Heckman (1979) approach. The inverse Mills ratio is then included as a control 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 joint normality of the error terms. In this semi-parametric approach, selection into employment implies that:

\[ E \left[ \epsilon_{it} | \Delta MTR_{it}, \Delta ATI_{it}, \Delta TLI_{it}, X_{it}, \alpha_t, \text{Work}_{i,t+1} = 1 \right] = \lambda(W_{it}', \zeta) \]  

where \( W \) includes our instruments for the intensive labor supply equation, the selection instrument, and all exogenous variables in equation (1). 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).

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 period \( t+1 \) labor earnings. These predicted tax variables are then used to estimate the extensive margin equation for all individuals in our sample.

To summarize, while the labor and tax literatures have typically estimated intensive margin or extensive margin equations in isolation of the other, we show that there are significant advantages to combining both equations. 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 period $t + 1$ in the extensive margin equation.

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 B. First, we estimate the selection equation (a variation of the extensive margin equation) and predict the selection adjustment term. Second, we estimate the intensive labor supply equation using 2SLS, conditioning on the selection adjustment term. Because the selection adjustment term is estimated, we use a clustered (by household) bootstrap procedure for inference which accounts for the inclusion of an estimated selection term in the intensive margin equation. We report 95% confidence intervals. Third, we use the parameter estimates from this equation to predict labor earnings for the entire sample including those who do not work in period $t + 1$. We also estimate tax liabilities and after-tax labor earnings given these labor earnings estimates. Fourth, we estimate the extensive margin equation using the estimated after-tax labor earnings variable derived from the intensive margin equation.

5 Results

Before discussing the regression results, we provide graphical evidence relating the predicted after-tax labor income measure to the probability of working. We compute the predicted increase in after-tax labor income between 2001 and 2009 and relate this to the change in the probability of working in 2001 and 2009 (conditional on working in 1999 and
2007, respectively). Figure 4 shows this relationship. For men and women, the probability of working increases monotonically with the predicted increase in after-tax labor income. In Appendix Figure E.1, we repeat this exercise for the change from 2001 and 2005 (which bookend the major tax changes in our sample) to show that this result is not driven by the Great Recession or the Making Work Pay Tax Credit in effect for tax years 2009 and 2010.

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 Heckman selection adjustment method; (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. Column (1) shows the results from a probit regression of the effect of the excluded tax variable (predicted after-tax labor income) on labor force participation for women. 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 observe few differences in the results across the estimation methods. For women, we find that the selection instrument positively predicts labor force participation in the next period. This relationship is statistically significant and varies independently in relation to the marginal net-of-tax rate and after-tax income variables. The coefficients on the other tax variables are close to zero and statistically insignificant.

In the corresponding estimates for men, we also find that the selection instrument is positively and statistically significantly associated with labor force participation. This relationship holds regardless of the estimation method that is used. For both men and women, 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 C (see Appendix Table E.1).

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. For women, we estimate an elasticity of -0.137 when no selection adjustment is made (Column (1)), -0.207 when a Heckman adjustment is made (Column (2)), and 0.080 when the semi-parametric adjustment is made (Column (3)). This last estimate implies that a 10% increase in the marginal net-of-tax rate increases labor
earnings by 0.8%. For men, we estimate elasticities of 0.398, 0.153, and 0.220, respectively. While the estimates using the semi-parametric adjustment are the expected sign, they are not statistically distinguishable from zero. The confidence intervals in this table are large, likely due to the relatively high variance of labor earnings for this population. While our estimates do not allow us to reject that older workers do not respond to changes in taxes on the intensive margin, we are also unable to rule out rather large elasticities. The point estimates are on the lower 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) estimate an elasticity of 0.4, and Singleton (2011) estimates an elasticity of 0.2 to 0.3. Our income effect estimates are also generally the expected sign though they are also statistically insignificant due to large standard errors.

Accounting for possible selection bias has advantages in our empirical approach beyond estimating consistent coefficients for the marginal net-of-tax rate and after-tax income variables. The selection adjustment allows for consistent estimation of all the parameters in the intensive margin equation. This is critical because we use the parameters from estimating the intensive margin equation to generate predicted labor earnings for the extensive margin equation. These predicted earnings are a function of all covariates included in the specification, and it is possible that selection may bias the coefficients estimated for other included variables, and consequently, the labor earnings predictions that are generated from this equation. Our selection corrections address this concern.

5.3 Extensive Margin

After using the intensive margin equation to predict labor earnings in period $t + 1$ for everyone in the sample, including individuals not working in period $t$, we then calculate the additional taxes that the individual would pay (had they worked) in that period.
The additional after-tax earnings due to working is the main endogenous variable in our extensive margin equation. We also control separately for after-tax income, which is also endogenous.

Table 4 presents the instrumental variable estimates of the extensive margin equation using IV-Probit regression. We present average marginal effects for the sample. We find large effects on the probability of working in period \( t+1 \) conditional on working in period \( t \) for both men and women and these effects are statistically significant. The results are robust across the different selection methods. We estimate that a 10% increase in after-tax labor income increases the probability of labor force participation by 7.2 percentage points for women in our preferred specification (semi-parametric). We obtain similar estimates for men: a 10% increase in after-tax labor income increases the probability of labor force participation by 8.7 percentage points. The Appendix shows 2SLS results using a linear probability model (see Appendix Table E.2). The results are similar.

The implied elasticities are 0.985 for women and 1.201 for men. These elasticities refer to the labor force participation responsiveness with respect to changes in after-tax labor income. We compare these elasticities to estimates found in the literature, with the caveat that these comparisons are often difficult given the use of different methods and the use of different functional forms for the extensive margin tax variable. 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. More recently, Gelber and Mitchell (2011) estimates a participation elasticity of 0.41. 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

\[ 22 \text{Among individuals ages 55 to 75, the probability of working in the next period, conditional on working in the current period, is 0.734 for women and 0.723 for men. We use these probabilities to construct elasticities from the estimates from Table 4. We calculate these elasticities using } \frac{\hat{\beta} E}{P(\text{work})}. \]
outcome variable, where retirement is defined as having no labor earnings (i.e., not working) and self-reporting as “retired.” We use retirement as a measure of a more permanent labor force participation effect. These estimates are presented in Table 5. Analogous linear probability model results are found in Appendix Table E.3. We find large effects on retirement decisions for women. Our estimates imply that a 10% increase in after-tax labor income reduces the probability of retirement by 5.6 percentage points, significant at the 10% level. Our retirement measure is a special case of “not working.” Over 77% of the tax effect on increasing the probability of labor force participation in Table 4 is driven by a reduction in retirement for women. For men, we find no statistically significant effects on retirement and the point estimates are near zero. Overall, we find evidence that changes in the tax code may have more permanent effects on the labor supply of older women.

5.4 Policy Simulations

The key finding in our analysis is that labor force participation is highly responsive to the additional taxes that older individuals would have to pay if they worked. 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 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. Instead, we note that the following estimates are lower bounds 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.\textsuperscript{23} We assume that an equivalent lump sum tax is levied on each person such that we can ignore income effects. For each person, we predict (1) the probability of working under period $t + 1$ tax rules and (2) the probability of working under the “counterfactual” tax rules (i.e., eliminating the employee portion of the payroll tax), substituting in:

$$\ln \left[ L_{i,t+1} - T_{i,t+1}^c (L_{i,t+1} + y_{i,t+1}^o) + T_{i,t+1}^c (y_{i,t+1}^o) \right],$$

where $T_{i,t+1}^c$ represents the counterfactual tax burden in period $t + 1$ 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, 73.4% of working women and 72.3% of working men earn positive wages two years later. Elimination of the employee FICA taxes would increase this percentage by 7.4 percentage points for women and 9.0 percentage points for men. This is a 10% increase in the probability of working for women and a 12% increase for men. We further estimate that there would be a 6.2 percentage point drop in retirement for women, representing a 39% decrease from baseline. Laitner and Silverman (2012) find that the elimination of the full payroll tax would, on average, extend working lives by one year. Our estimates imply smaller changes,\textsuperscript{24} but these effects are still economically significant.

Our second policy experiment expands the EITC to the 65+ population while eliminating the dependents requirement. We implement this policy on our 65+ sample, again assuming that an equal lump sum tax is levied. We apply the EITC schedule for 2009, the latest year in our sample.\textsuperscript{25} In 2009, the credit was phased-in at a rate of 45% up to $12,570

\begin{footnotesize}
\begin{itemize}
\item \textsuperscript{23}Laitner and Silverman (2012) eliminates both the employee and employer portions.
\item \textsuperscript{24}We assume that the individuals incentivized to work in period $t + 1$ work, on average, 2 years longer than they would have. Given this assumption, we would need to estimate much larger effects to predict an average increased working life of one year.
\item \textsuperscript{25}We use the most generous benefit schedule available in 2009 – the schedule for individuals with three children.
\end{itemize}
\end{footnotesize}
of earned income for a maximum benefit of $5,657. The benefit remained constant between $12,570 to $16,450. At $16,450 of earnings, the credit was phased out at a rate of 21.06%, implying that no credit was received at an income of $43,279 or higher. Table 7 presents the results from this simulation. We estimate that this policy would increase the probability that a female worker remains in the labor force by 9.8 percentage points. The probability that a male worker would stay in the labor force would increase by 8.0 percentage points. These represent increases of 13% and 11% from baseline, respectively. We also again find proportional reductions in retirement probabilities for women. Note that 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.

We find that the two policies would have significant effects on labor force participation. We also compare the loss in taxes associated with each policy (ignoring the implied lump sum taxes imposed in each case). Our calculation for the estimated per-person tax loss uses the calculated tax losses for each person minus the additional taxes collected because of the increased labor force participation.\footnote{These additional collected taxes include the employer portion of the FICA taxes.} We estimate that, on average, women ages 65+ would pay $901 less in taxes under the payroll tax reform and $1,511 less due to the EITC expansion per year. Men would pay $1,072 less in taxes under the payroll tax reform and $1,056 less under the EITC expansion policy.

### 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 selected 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, in columns 3 and 4 of Panel A, we replicate the analysis excluding 2009 data. These results check the robustness of our results to excluding the period of the Great Recession. The Great Recession may have impacted labor supply decisions differentially during that time period, confounding our estimates. Our extensive margin and policy simulation estimates are slightly larger when we exclude 2009 but, overall, the results are generally similar. The robustness of our results to the exclusion of 2009 is suggestive that our empirical strategy adequately accounts for differential trends.

Third, we allow the effects of initial income to vary by year by interacting both initial labor earnings and initial non-labor income with year dummies. This test accounts for the possibility that mean reversion effects or trends vary by year. We present these results in columns 5 and 6 of Panel A. We find little evidence that year-specific trends are important in explaining the results, again suggesting that our empirical strategy accounts for trends and mean reversion concerns. In Appendix Table E.4, we also include more flexible non-labor income controls and find consistent results.

Fourth, in columns 1 and 2 of Panel B, we present results using nonlinear least squares (i.e., Poisson regression) to estimate the intensive margin equation. In our main specification, we used a log-linear form both because it is standard in the literature and because the techniques to adjust for selection are well-studied for linear specifications. However, there are two advantages to using a Poisson regression. First, Silva and Tenreyro (2006) show that Poisson regressions allow for a more flexible structure of the error term whereas a log-linear form assumes that the error term is multiplicative in labor earnings. Second,
when predicting labor earnings for each person in our sample after estimation of equation (1), there are known problems with taking the exponential of the expectation of a log. Instead of estimating and predicting the log of labor earnings and then taking the exponential of this prediction, we can model labor earnings directly as an exponential of the explanatory variables. We estimate the intensive margin equation using IV-Poisson. The instruments are the same as the ones used for our main specifications.\footnote{After estimating the intensive margin equation, we must estimate the constant. In our main specifications, we used the technique suggested in Heckman (1990). We modify this technique here to account for the change in the functional form of the specification. Our extension margin estimation, then, proceeds as before.} When we use nonlinear least squares, we find a statistically significant effect for men on the intensive margin. However, the other results are very similar to those using 2SLS, suggesting that use of the log-linear specification is not biasing our extensive margin results. We find slightly larger effects for the payroll tax reform and slightly smaller results for the EITC expansion.

Fifth, in columns 3 and 4 of Panel B in Table 8, we present results where we “trim” the outcome variable in the intensive margin equation. This trimming eliminates large changes in labor earnings (e.g., full- to part-time transitions) to ensure that labor decisions resulting in large changes in labor earnings are not driving our results. We reassign labor earnings representing large decreases to 75% of initial labor earnings, and we reassign large increases to 125% of initial labor earnings. The results in Table 8 suggest that large changes in labor earnings are not driving our results. In Appendix Table E.5, we further explore concerns regarding full-time to part-time transitions and find little evidence that such transitions are important in explaining our results.\footnote{In principle, we could also explicitly model part-time work and include an additional equation in our empirical model with this outcome variable. We would then create an equivalent instrument for the pecuniary incentives to work part-time (versus full-time) and predict transitions between full-time and part-time work. However, this idea is difficult to implement in practice given that we observe relatively few such transitions from full-time to part-time work in our data (we observe 695 such transitions for women and 580 for men over the ten year period) and given the additional burden on the data of identifying another equation. Instead, we show that our model of intensive labor supply decisions uses tax variables that adequately explain the observed variation in labor earnings, even large changes due to transitions to part-time work.}
Finally, in columns 5 and 6 of Panel B in Table 8, we control for age and year interactions using the following age categories: 55-62, 63, 64, 65, 66+. We perform this analysis to control for changes in Social Security policy, which were based on age, over this period. For example, the Social Security Earnings Test was eliminated for ages 65-69 in 2000 and the full retirement age gradually changed during our sample period. We find consistent results when we control more explicitly for age-year interactions. We also test for the importance of the Earnings Test policy change in Appendix Table E.4 by excluding the 1999-2001 sample. Again, we find little evidence that this policy change is confounding our estimates. Overall, these results suggest that our identification sources are orthogonal to contemporaneous changes in Social Security policy.

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. We model intensive labor supply as a function of the marginal net-of-tax rate and after-tax income. Extensive labor supply is modeled as a function of the monetary benefit of working as measured by after-tax labor earnings. 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 estimates are similar or larger in magnitude than estimates found in the literature on extensive margin effects for younger ages. These findings suggest scope for extending the working lives of older workers through the tax code. We also find evidence that women retire in response to higher taxes, implying the possibility that some older workers exit the labor force more permanently when taxes increase. 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. First, we estimate that eliminating the employee portion of the payroll tax would decrease the percentage of working women that leave the labor force by 7.4 percentage points and the percentage of working men by 9.0 percentage points. Second, we simulate effects of expanding EITC to older ages and estimate that this reform would increase labor force participation of older female workers by 9.8 percentage points and the participation of older male workers by 8.0 percentage points. 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.
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.
We do not include the 2009 Making Work Pay Tax Credit in this figure since the credit size was dependent on labor earnings. In 2009, the Making Work Pay Tax Credit provided a tax credit up to $400 for single heads of households and up to $800 for married couples filing jointly. The credit increased labor earnings by 6.2 percent up to the maximum and was phased out at higher levels of income.
Figure 4: Change in the Probability of Working by Percentage Change in Predicted After-Tax Labor Income: 2001 to 2009

Notes: The y-axis is the change in the probability of working between 2001 and 2009 for each bin (i.e., the fraction working in 2009 minus the predicted fraction working in 2001 based on covariates). The predicted log of after-tax labor income instrument in 2009 is calculated for each 2009 observation. We also calculate each person’s predicted log of after-tax labor income under the 2001 tax schedule. We group individuals into bins based on the change in the predicted after-tax labor income between 2001 and 2009.

This approach parallels our empirical strategy closely. The x-axis is based on the change in after-tax labor income, holding everything about an individual constant, such that changes are driven entirely by legislative tax schedule changes. The y-axis is the change in the probability of working based on covariates. The instrument uses predicted (based on covariates) earnings and non-labor income to generate the predicted taxes. The figure above looks at the change in taxes for a fixed $X$ (and creates bins accordingly) and the change in the probability of working for a fixed $X$. 
### Table 1: Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Men</th>
<th>Women</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>62.0</td>
<td>61.7</td>
</tr>
<tr>
<td>Less than HS</td>
<td>15.6%</td>
<td>13.1%</td>
</tr>
<tr>
<td>HS Grad</td>
<td>32.6%</td>
<td>39.0%</td>
</tr>
<tr>
<td>Some College</td>
<td>21.2%</td>
<td>25.7%</td>
</tr>
<tr>
<td>College Grad</td>
<td>30.6%</td>
<td>22.2%</td>
</tr>
<tr>
<td><strong>Labor Outcomes</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Personal Labor Earnings</td>
<td>$43,346.47</td>
<td>$25,097.61</td>
</tr>
<tr>
<td>Work in Next Period</td>
<td>72.3%</td>
<td>73.4%</td>
</tr>
<tr>
<td>Wages in Next Period if Work</td>
<td>$49,875.79</td>
<td>$30,850.33</td>
</tr>
<tr>
<td>Retired in Next Period</td>
<td>15.6%</td>
<td>16.1%</td>
</tr>
<tr>
<td>Total Household Income</td>
<td>$109,541.40</td>
<td>$80,315.34</td>
</tr>
<tr>
<td><strong>Tax Variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marginal Tax Rate</td>
<td>27.8</td>
<td>26.0</td>
</tr>
<tr>
<td>Change in MTR</td>
<td>-3.5</td>
<td>-3.5</td>
</tr>
<tr>
<td>N</td>
<td>8,517</td>
<td>9,357</td>
</tr>
</tbody>
</table>

Notes: All dollar values expressed in 2009 dollars.
Table 2: Selection Equation

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Women</th>
<th>I(Work)</th>
<th>Men</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Predicted $\Delta$ in $\ln(1 - \text{Marginal Tax Rate})$</td>
<td>0.011</td>
<td>-0.046</td>
<td>0.047**</td>
</tr>
<tr>
<td></td>
<td>[-0.035, 0.057]</td>
<td>[-0.124, 0.031]</td>
<td>[0.001, 0.094]</td>
</tr>
<tr>
<td>Predicted $\Delta$ in $\ln(\text{After-Tax Income})$</td>
<td>0.0255</td>
<td>-0.107</td>
<td>-0.556***</td>
</tr>
<tr>
<td></td>
<td>[-0.181, 0.230]</td>
<td>[-0.298, 0.084]</td>
<td>[-0.783, -0.328]</td>
</tr>
<tr>
<td>Predicted $\ln(\text{After-Tax Labor Income})$</td>
<td>0.116***</td>
<td>0.148***</td>
<td>0.129***</td>
</tr>
<tr>
<td></td>
<td>[0.046, 0.186]</td>
<td>[0.050, 0.246]</td>
<td>[0.077, 0.181]</td>
</tr>
<tr>
<td>Probit</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Monotone Rank</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>9,357</td>
<td>9,357</td>
<td>8,517</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% Confidence Intervals in brackets estimated using clustered (by household) bootstrap. Coefficients are scaled so that sum of the square of the coefficients is equal to 1. Other variables included: year dummies; interactions based on age group $\times$ education; spousal age group fixed effects; indicator variables for white, black, and Hispanic. Initial income controls include 20 indicator variables based on initial labor earnings, a 20-piece spline based on initial labor earnings, and controls for initial spousal earnings and total non-labor income.

Table 3: Intensive Labor Supply Equation, 2SLS

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Women</th>
<th>ln(Labor Income)</th>
<th>Men</th>
<th>Semi-Parametric</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>None</td>
<td>Heckman</td>
<td>Semi-Parametric</td>
<td>None</td>
</tr>
<tr>
<td>Selection Adjustment:</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>$\Delta \ln(1 - \text{MTR})$</td>
<td>-0.137</td>
<td>-0.207</td>
<td>0.080</td>
<td>0.398</td>
</tr>
<tr>
<td></td>
<td>[-0.586, 0.312]</td>
<td>[-0.734, 0.319]</td>
<td>[-0.838, 0.997]</td>
<td>[-0.294, 1.091]</td>
</tr>
<tr>
<td>$\Delta \ln(\text{After-Tax Income})$</td>
<td>-0.050</td>
<td>-0.006</td>
<td>-0.002</td>
<td>-1.779*</td>
</tr>
<tr>
<td>Observations</td>
<td>6,867</td>
<td>6,867</td>
<td>6,867</td>
<td>6,154</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% Confidence Intervals in brackets estimated using clustered (by household) bootstrap. Other variables included: year dummies; interactions based on age group $\times$ education; spousal age group fixed effects; indicator variables for white, black, and Hispanic. Initial income controls include 20 indicator variables based on initial labor earnings, a 20-piece spline based on initial labor earnings, and controls for initial spousal earnings and total non-labor income.
Table 4: Extensive Labor Supply Equation (Working), IV-Probit

<table>
<thead>
<tr>
<th>Selection Adjustment:</th>
<th>Women</th>
<th>I(Work)</th>
<th>Men</th>
<th>Semi-Parametric</th>
<th>Women</th>
<th>I(Work)</th>
<th>Men</th>
<th>Semi-Parametric</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(After-Tax Labor Income)</td>
<td>None</td>
<td>0.693***</td>
<td>Heckman</td>
<td>0.802***</td>
<td>Semi-Parametric</td>
<td>0.723**</td>
<td>None</td>
<td>0.866***</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>[0.130, 1.256]</td>
<td>(2)</td>
<td>[0.162, 1.442]</td>
<td>(3)</td>
<td>[0.102, 1.345]</td>
<td>(4)</td>
<td>[0.370, 1.362]</td>
</tr>
<tr>
<td>ln(After-Tax Income)</td>
<td>0.047</td>
<td>0.050</td>
<td>0.036</td>
<td>0.051*</td>
<td>0.043</td>
<td>0.048</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7)</td>
<td>[-0.032, 0.125]</td>
<td>(8)</td>
<td>[-0.025, 0.125]</td>
<td>(9)</td>
<td>[-0.035, 0.107]</td>
<td>(10)</td>
<td>[-0.008, 0.110]</td>
</tr>
<tr>
<td>Observations</td>
<td>9,357</td>
<td>9,357</td>
<td>9,357</td>
<td>8,517</td>
<td>8,517</td>
<td>8,517</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. Average marginal effects for sample reported. 95% Confidence Intervals in brackets adjusted for household-level clustering. Other variables included: year dummies; interactions based on age group × education; spousal age group fixed effects; indicator variables for white, black, and Hispanic. Initial income controls include 20 indicator variables based on initial labor earnings, a 20-piece spline based on initial labor earnings, and controls for initial spousal earnings and total non-labor income.

Table 5: Extensive Labor Supply Equation (Retirement), IV-Probit

<table>
<thead>
<tr>
<th>Selection Adjustment:</th>
<th>Women</th>
<th>I(Retire)</th>
<th>Men</th>
<th>Semi-Parametric</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(After-Tax Labor Income)</td>
<td>None</td>
<td>-0.536***</td>
<td>Heckman</td>
<td>-0.622**</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>[-1.070, -0.003]</td>
<td>(2)</td>
<td>[-1.230, -0.014]</td>
</tr>
<tr>
<td>ln(After-Tax Income)</td>
<td>-0.062**</td>
<td>-0.065**</td>
<td>-0.054*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3)</td>
<td>[-0.125, -0.002]</td>
<td>(4)</td>
<td>[-0.128, -0.001]</td>
</tr>
<tr>
<td>Observations</td>
<td>9,357</td>
<td>9,357</td>
<td>9,357</td>
<td>8,517</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. Average marginal effects for sample reported. 95% Confidence Intervals in brackets adjusted for household-level clustering. Other variables included: year dummies; interactions based on age group × education; spousal age group fixed effects; indicator variables for white, black, and Hispanic. Initial income controls include 20 indicator variables based on initial labor earnings, a 20-piece spline based on initial labor earnings, and controls for initial spousal earnings and total non-labor income.

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>0.074**</td>
<td>0.090**</td>
<td>-0.062*</td>
<td>-0.005</td>
</tr>
<tr>
<td>Baseline Rate</td>
<td>0.734</td>
<td>0.723</td>
<td>0.161</td>
<td>0.156</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 adjusted for household-level clustering.
<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>0.098***</td>
<td>0.080***</td>
<td>-0.073***</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td>[0.031, 0.165]</td>
<td>[0.041, 0.120]</td>
<td>[-0.117, -0.028]</td>
<td>[-0.096, 0.084]</td>
</tr>
<tr>
<td>Baseline Rate</td>
<td>0.734</td>
<td>0.723</td>
<td>0.161</td>
<td>0.156</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 adjusted for household-level clustering.
### Table 8: Robustness Tests

#### Panel A: Robustness Tests

<table>
<thead>
<tr>
<th>Specification:</th>
<th>Main Results</th>
<th>Pre-2009 Only</th>
<th>Income × Year Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Women</td>
<td>Men</td>
<td>Women</td>
</tr>
<tr>
<td><strong>1. Intensive Margin Equation - Outcome is $\Delta \ln(\text{Labor Income})$</strong></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>$\Delta \ln(1-MTR)$</td>
<td>0.080</td>
<td>0.220</td>
<td>-0.260</td>
</tr>
<tr>
<td></td>
<td>[-0.838, 0.997]</td>
<td>[-0.437, 0.876]</td>
<td>[-0.739, 0.220]</td>
</tr>
<tr>
<td><strong>2. Extensive Margin Equation - Outcome is I(Work)</strong></td>
<td>(5)</td>
<td>(6)</td>
<td></td>
</tr>
<tr>
<td>$\ln(\text{After-Tax Labor Income})$</td>
<td>0.723**</td>
<td>0.868***</td>
<td>0.867**</td>
</tr>
<tr>
<td></td>
<td>[0.102, 1.345]</td>
<td>[0.324, 1.412]</td>
<td>[0.138, 1.597]</td>
</tr>
<tr>
<td><strong>3. Simulations - Outcome is $P(\text{Working in } t+1)$</strong></td>
<td>(7)</td>
<td>(8)</td>
<td>(9)</td>
</tr>
<tr>
<td>Payroll Tax Simulation</td>
<td>0.074**</td>
<td>0.090**</td>
<td>0.089*</td>
</tr>
<tr>
<td></td>
<td>[0.003, 0.145]</td>
<td>[0.016, 0.164]</td>
<td>[-0.009, 0.187]</td>
</tr>
<tr>
<td>EITC Simulation</td>
<td>0.098***</td>
<td>0.108***</td>
<td>0.091***</td>
</tr>
<tr>
<td></td>
<td>[0.031, 0.165]</td>
<td>[0.041, 0.120]</td>
<td>[0.073, 0.109]</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% Confidence intervals in brackets estimated adjusted for clustering at household-level. 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) exclude the 2009 data from the analysis. Columns (5) and (6) interact the initial labor and non-labor income controls with year fixed effects.
Panel B: Robustness Tests (Continued)

<table>
<thead>
<tr>
<th>Specification:</th>
<th>Nonlinear Trimmed Include Age</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Least Squares</td>
<td>Labor Earnings</td>
<td>Interactions</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td></td>
<td>Women</td>
<td>Men</td>
<td>Women</td>
</tr>
<tr>
<td><strong>1. Intensive Margin Equation - Outcome is Δln(Labor Income)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δln(1-MTR)</td>
<td>0.079</td>
<td>0.062</td>
<td>-0.245</td>
</tr>
<tr>
<td></td>
<td>[-0.554, 0.712]</td>
<td>[0.067, 1.347]</td>
<td>[-0.142, 0.153]</td>
</tr>
<tr>
<td><strong>2. Extensive Margin Equation - Outcome is I(Work)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(After-Tax Labor Income)</td>
<td>0.897***</td>
<td>0.860**</td>
<td>1.045***</td>
</tr>
<tr>
<td></td>
<td>[0.280, 1.513]</td>
<td>[0.251, 1.621]</td>
<td>[0.151, 1.587]</td>
</tr>
<tr>
<td><strong>3. Simulations - Outcome is P(Working in t+1)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Payroll Tax Simulation</td>
<td>0.093**</td>
<td>0.088**</td>
<td>0.108**</td>
</tr>
<tr>
<td></td>
<td>[0.049, 0.176]</td>
<td>[0.020, 0.177]</td>
<td>[0.005, 0.171]</td>
</tr>
<tr>
<td>EITC Simulation</td>
<td>0.060***</td>
<td>0.120***</td>
<td>0.085***</td>
</tr>
<tr>
<td></td>
<td>[0.029, 0.132]</td>
<td>[0.041, 0.113]</td>
<td>[0.053, 0.200]</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% Confidence intervals in brackets estimated adjusted for clustering at household-level. 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) estimates intensive margin equation using nonlinear least squares.
Columns (3) and (4) reassign labor earnings in period $t+1$ that are over 25% larger than labor earnings in $t$ to 125% of initial labor earnings. Labor earnings in period $t+1$ that are under 75% of labor earnings in period $t$ are reassigned to 75% of initial labor earnings.
Columns (5) and (6) include indicators for age groups <62, 63, 64, 65, 66+ each interacted with year dummies.
Appendix

A Income Effect

The Gruber and Saez (2002) after-tax income variable is $\ln(y_{i,t+1} - T_{t+1}(y_{i,t+1})) - \ln(y_{i,t} - T_{t}(y_{i,t}))$ and the paper models changes in taxable income as a function of this variable. This structural relationship may be problematic. Households respond to shifts in their budget constraints, but the Gruber and Saez (2002) variable assumes that they are responding to their final after-tax income, which includes the response to the budget constraint shift and changes in the marginal tax rate. Instrumental variable techniques do not solve this problem. This point is discussed in Powell and Shan (2012), and we model after-tax income in the same manner. An example can help make this point clearer. Imagine an individual with income $\tilde{y}$ in period 1 and no tax liability. The tax code changes such that this person is given a lump sum equal to $\tilde{y}$ in period 2. In response, the person changes behavior and earns income equal to 0. This is a strong income effect (i.e., income targeting) resulting from the outward budget constraint shift. However, the Gruber-Saez specification models the change in earnings ($-\tilde{y}$) as a function of the final change in after-tax income, which is 0. This is because using actual after-tax income changes includes the response to the tax change as well. The variable capturing the income effect should not include this endogenous response, only the budget constraint shift.

We include an after-tax income term because our shocks to the marginal net-of-tax rate also shock the individual’s budget constraint. Our after-tax income term is the expected change in after-tax income given legislative changes in the tax schedule only. We hold everything constant and estimate the budget constraint shift due only to these changes. This separates the substitution and income effects as before, and we interpret our estimates as compensated elasticities.

We expect the coefficient on our income variable to be negative in the intensive
labor supply equation. On the extensive margin, we follow a similar technique. Our endogenous variable uses initial household income with shifts due to legislative tax schedule changes.

B Implementation Details

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

B.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

\[ P(\text{Work}_{i,t+1} = 1) = F\left( \phi_t + X_{it}'\gamma + \beta_1 \Delta \text{MTR}_{it} + \beta_2 \Delta \text{ATI}_{it} + \beta_3 \Delta \text{ATLI}_{it}, \eta \right) \]  

(4)

The predictions provided by equation (4) are used as selection adjustments for the intensive equation. We do this in two different ways. First, we assume that \( F(\cdot) = \Phi(\cdot) \), estimate equation (4) using a probit regression, and form an inverse Mills ratio as discussed in Heckman (1979). This method is frequently used in the literature.

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 \( W_{it}'\hat{\zeta} \).

\[29\] The advantage of this approach is that the maximum rank estimator requires no

\[29\]Newey (2009) recommends the use of a spline over a power series.
distributional assumptions to obtain consistent $\hat{\zeta}$.

To implement the monotone rank estimator, we generated initial values through a probit regression and maximized the objective function using an MCMC optimization algorithm (see Chernozhukov and Hong (2003)). Standard errors are generated using a clustered bootstrap.\(^\text{30}\)

### B.2 Step 2:

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

\[
\ln L_{i,t+1} - \ln L_{it} = \alpha_t + X_{it}' \delta + \beta^I \left[ \ln(1 - \tau_{i,t+1}) - \ln(1 - \tau_{it}) \right]
+ \theta^I \left[ \ln (y_{it} - T_{i+1}(y_{it})) - \ln (y_{it} - T_{i}(y_{it})) \right] + \lambda(W_{it}' \hat{\zeta}) + \mu_{it}
\]

where $\epsilon_{it} = \lambda(W_{it}' \zeta) + \mu_{it}$. In practice, we use an inverse Mills ratio or a 5-piece spline in $W_{it}' \hat{\zeta}$. We use $\Delta MTR_{it}$ and $\Delta ATI_{it}$ as instruments.

We bootstrap Steps 1 and 2 to account for the inclusion of an estimated term in equation (5). Since each household may be included multiple times in our data, we use a clustered bootstrap.

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 the change in 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 for period $t+1$.

We use 2SLS to obtain consistent estimates. Once we have consistent estimates for equation (5), we can predict $\ln L_{i,t+1} - \ln L_{it}$ for our entire sample. This includes people who

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\(^{30}\)Subbotin (2007) discusses properties of bootstrapping rank regression estimates.
did not work in period $t + 1$. However, it is important to note that 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 the change in earnings for the entire sample using the estimated coefficients in equation (5), the estimated constant term, and the imputed change in $\ln(1 - \tau_{i,t+1}) - \ln(1 - \tau_{it})$. In other words, we have consistent predictions of the tax variables and the coefficients to predict $\ln L_{i,t+1} - \ln L_{it}$ for everyone in our sample. We use this to predict $L_{i,t+1}$ using

$$
\hat{L}_{i,t+1} = \exp(\ln L_{it} + \ln \hat{L}_{i,t+1} - \ln L_{it}).
$$

(B.3) Step 3:

Once we have $\hat{L}_{i,t+1}$, we can calculate $\hat{T}(y^o + \hat{L})$ using NBER’s TAXSIM program. Then, we can construct the after-tax labor income measure:

$$
\ln \left( \hat{L}_{i,t+1} - \hat{T}_{t+1}(y^o_{i,t+1} + \hat{L}_{i,t+1}) + T(y^o_{i,t+1}) \right)
$$

(B.4) Step 4:

Next, we estimate

$$
P(\text{Work}_{i,t+1} = 1) = F\left( \phi_t + X^\prime_{it}\gamma + \beta^E \ln \left( \hat{L}_{i,t+1} - \hat{T}_{t+1}(y^o_{i,t+1} + \hat{L}_{i,t+1}) + T(y^o_{i,t+1}) \right) + \theta^E \left[ \ln (y_{it} - T_{t+1}(y_{it})) \right] + \nu_{i,t+1} \right).$$

We estimate this equation using the IV-Probit technique introduced in Rivers and Vuong (1988) (referred to as two-stage conditional maximum likelihood (2SCML) in the
paper) with instruments $\hat{\text{ATLI}}_{it}$ and $\hat{\text{ATI}}_{it}$. 2SLS results provide similar results and are provided in Appendix Section E.

C First Stage

Table E.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. We find strong first-stage relationships for both women and men. The partial F-statistic for the marginal net-of-tax rate variable is 130.5 for women and 97.9 for men. The partial F-statistic for the after-tax income variable is 31748.9 for women and 34591.6 for men.\(^{31}\) Thus, the first-stage relationships are suitably strong by conventional cut-offs (Staiger and Stock (1997)).

D Part-Time Work Transitions

It is possible that there are additional margins that our intensive and extensive equations do not capture. Workers may make intensive labor supply decisions which depend on income taxes but cannot be summarized by the marginal net-of-tax rate and after-tax income alone. For example, decisions to transition into part-time work may not be based purely on the marginal net-of-tax rate, but rather the reduction in after-tax labor income from transitioning from full-time to part-time work. This possibility is not necessarily problematic if changes in the tax-driven incentives on these omitted margins are orthogonal to changes in the budget constraint traced out by the included variables.

These discrete labor supply transitions are only problematic for estimating the intensive margin if they are: (a) tax-driven and (b) not adequately explained by the included tax variables in our main specification. We test for this in a few different ways. In columns

\(^{31}\)The large F-statistics for the after-tax income variable partially reflect the construction of this variable, as described in Appendix Section A. Both the endogenous variable and instrument focus on the budget constraint shift due to legislative tax schedule changes.
3 and 4 of Panel B in Table 8, we presented results where we “trim” the outcome variable in the intensive margin equation. This trimming eliminates large changes in labor earnings (i.e., full- to part-time transitions) to ensure that labor decisions resulting in large changes in labor earnings are not driving our results.

We can also study the relationship between our instruments (the predicted change in the marginal-net-of-tax-rate and predicted change in after-tax income) and part-time work directly. While it would not be surprising to find a relationship since transitions into part-time work may depend on the marginal net-of-tax rate, the absence of a relationship would suggest that our tax variables are not systematically correlated with other tax-driven intensive labor supply decisions. We present the results of this test in Table E.5. We find no statistically significant relationship.

Intensive margin decisions that are not captured by the marginal net-of-tax rate and after-tax income do not appear to be driving our final results. While we may believe that labor decisions are impacted by taxes in ways other than the marginal tax rate and tax liability, our contribution to the literature is modeling a crucial missing component in much of the literature - the tax-based incentive to participate in the labor force. Our empirical analysis suggests that our two equations are useful for understanding a rich set of labor outcomes related to the tax code.
E Appendix Figures and Tables

Figure E.1: Change in the Probability of Working by Percentage Change in Predicted After-Tax Labor Income: 2001 to 2005

Notes: The y-axis is the change in the probability of working between 2001 and 2005 for each bin (i.e., the fraction working in 2005 minus the predicted fraction working in 2001 based on covariates). The predicted log of after-tax labor income instrument in 2005 is calculated for each 2005 observation. We also calculate each person’s predicted log of after-tax labor income under the 2001 tax schedule. We group individuals into bins based on the change in the predicted after-tax labor income between 2001 and 2005. Categories are different than those in Figure 4 because the 2009 Making Work Pay Tax Credit increased predicted after-tax labor income. The instrument is smaller in 2005 and our categories reflect this overall reduction.
### Table E.1: Intensive Labor Supply Equation, First Stage

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Δ ln(1-MTR)</th>
<th>Δ ln(After-Tax Income)</th>
<th>Δ ln(1-MTR)</th>
<th>Δ ln(After-Tax Income)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted Δ ln(1-MTR)</td>
<td>0.567***</td>
<td>0.001</td>
<td>0.447***</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>[0.470, 0.664]</td>
<td>[-0.001, 0.003]</td>
<td>[0.358, 0.536]</td>
<td>[-0.002, 0.001]</td>
</tr>
<tr>
<td>Predicted Δ ln(After-Tax Income)</td>
<td>1.427***</td>
<td>0.986***</td>
<td>1.463***</td>
<td>0.988***</td>
</tr>
<tr>
<td></td>
<td>[0.926, 1.927]</td>
<td>[0.977, 0.995]</td>
<td>[0.764, 2.161]</td>
<td>[0.980, 0.996]</td>
</tr>
<tr>
<td>Partial F-Statistic</td>
<td>130.5</td>
<td>31748.9</td>
<td>97.9</td>
<td>34591.6</td>
</tr>
<tr>
<td>Sample</td>
<td>Women</td>
<td>Women</td>
<td>Men</td>
<td>Men</td>
</tr>
<tr>
<td>N</td>
<td>6,867</td>
<td>6,867</td>
<td>6,154</td>
<td>6,154</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% Confidence Intervals in brackets adjusted for household-level clustering. Other variables included: year dummies; interactions based on age group × education; spousal age group fixed effects; indicator variables for white, black, and Hispanic. Initial income controls include 20 indicator variables based on initial labor earnings, a 20-piece spline based on initial labor earnings, and controls for initial spousal earnings and total non-labor income.

### Table E.2: Extensive Labor Supply Equation (Employment), 2SLS

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>I(Work)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Selection Adjustment:</td>
<td>None</td>
</tr>
<tr>
<td>ln(After-Tax Labor Income)</td>
<td>0.678**</td>
</tr>
<tr>
<td></td>
<td>[0.113, 1.244]</td>
</tr>
<tr>
<td>ln(After-Tax Income)</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td>[-0.033, 0.114]</td>
</tr>
<tr>
<td>Observations</td>
<td>9,357</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% Confidence Intervals in brackets adjusted for household-level clustering. Other variables included: year dummies; interactions based on age group × education; spousal age group fixed effects; indicator variables for white, black, and Hispanic. Initial income controls include 20 indicator variables based on initial labor earnings, a 20-piece spline based on initial labor earnings, and controls for initial spousal earnings and total non-labor income.
<table>
<thead>
<tr>
<th>Selection Adjustment:</th>
<th>Women</th>
<th></th>
<th>Men</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>None</td>
<td>Heckman</td>
<td>Semi-Parametric</td>
<td>None</td>
</tr>
<tr>
<td>ln(After-Tax Labor Income)</td>
<td>-0.468**</td>
<td>-0.544**</td>
<td>-0.491*</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>[-0.920, -0.016]</td>
<td>[-1.062, -0.026]</td>
<td>[-0.990, 0.008]</td>
<td>[-0.429, 0.426]</td>
</tr>
<tr>
<td>ln(After-Tax Income)</td>
<td>-0.053**</td>
<td>-0.055*</td>
<td>-0.046*</td>
<td>-0.015</td>
</tr>
<tr>
<td></td>
<td>[-0.104, -0.001]</td>
<td>[-0.111, 0.001]</td>
<td>[-0.093, 0.002]</td>
<td>[-0.065, 0.034]</td>
</tr>
<tr>
<td>Observations</td>
<td>9,357</td>
<td>9,357</td>
<td>8,517</td>
<td>8,517</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% Confidence Intervals in brackets adjusted for household-level clustering. Other variables included: year dummies; interactions based on age group × education; spousal age group fixed effects; indicator variables for white, black, and Hispanic. Initial income controls include 20 indicator variables based on initial labor earnings, a 20-piece spline based on initial labor earnings, and controls for initial spousal earnings and total non-labor income.
Table E.4: Additional Robustness Checks

<table>
<thead>
<tr>
<th>Robustness Tests</th>
<th>No 1999-2001</th>
<th>More Flexible Controls for Non-Labor Income</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>Women</td>
<td>Men</td>
</tr>
<tr>
<td></td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>Women</td>
<td>Men</td>
</tr>
<tr>
<td>Intensive Margin Equation - Dependent Variable is Δ ln L</td>
<td>-0.465</td>
<td>0.508</td>
</tr>
<tr>
<td>[-1.108, 0.178]</td>
<td>[-0.219, 1.235]</td>
<td>[-0.092, 0.115]</td>
</tr>
<tr>
<td>Extensive Margin Equation - Dependent Variable is 1(Work)</td>
<td>1.448***</td>
<td>0.735*</td>
</tr>
<tr>
<td>[0.720, 2.177]</td>
<td>[-0.008, 1.479]</td>
<td>[0.01, 1.674]</td>
</tr>
<tr>
<td>Employed Tax Simulation</td>
<td>0.136***</td>
<td>0.077</td>
</tr>
<tr>
<td>[0.052, 0.221]</td>
<td>[-0.027, 0.157]</td>
<td>[-0.006, 0.189]</td>
</tr>
<tr>
<td>EITC Simulation</td>
<td>0.155***</td>
<td>0.079**</td>
</tr>
<tr>
<td>[0.0125, 0.186]</td>
<td>[0.01, 0.145]</td>
<td>[0.011, 0.245]</td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% Confidence Intervals in brackets adjusted for household-level clustering. 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) exclude the 1999-2001 sample.

Columns (3) and (4) include indicators based on bins for non-labor income to more flexibly control for independent effects of non-labor income.

Table E.5: Part-Time Work and Tax Instruments

<table>
<thead>
<tr>
<th></th>
<th>Women</th>
<th>Men</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted Δ ln(1-MTR)</td>
<td>-0.208</td>
<td>0.187</td>
</tr>
<tr>
<td>[-1.781, 1.364]</td>
<td>[-0.922, 1.295]</td>
<td></td>
</tr>
<tr>
<td>Predicted Δ ln(After-Tax Income)</td>
<td>2.616</td>
<td>-0.277</td>
</tr>
<tr>
<td>[-1.373, 6.604]</td>
<td>[-5.620, 5.067]</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Significance Levels: *10%, **5%, ***1%. 95% Confidence Intervals in parentheses estimated using clustered (by household) bootstrap. Other variables included: year dummies; interactions based on age group × education; spousal age group fixed effects; indicator variables for white, black, and Hispanic. Initial income controls include 20 indicator variables based on initial labor earnings, a 20-piece spline based on initial labor earnings, and controls for initial spousal earnings and total non-labor income. Semi-parametric selection adjustment used.