ESSAYS ON RESPONSES TO INCOME TAXATION IN THE UNITED STATES

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ABSTRACT

Federal income taxes on individual income in the United States raised over $1.5 trillion in revenue in 2015. This represents approximately half of all tax revenue collected by the federal government. Returns to saving and working are affected by income taxes, and understanding the responses of individuals to them is crucial to evaluating their welfare and revenue consequences. In this dissertation, I study individual income responses to federal income taxes in the United States.

In the first chapter, I estimate the responsive of capital gains realizations and ordinary income in the United States to changes in marginal tax rates on both types of income. I use a large non-public panel of federal income tax returns from 1997-2007, and find two key results, though both are sensitive to a variety of specification decisions. First, capital gains respond to both the capital gains tax rate and the ordinary income tax rate. Second, I find mixed evidence that ordinary income responds to the ordinary income tax rate and the long-term capital gains tax rate. These results suggest cross-tax responses between these two bases are important, and should not be ignored when estimating taxpayer responses in the United States.

The second chapter investigates how taxpayers respond to changes within the tax schedule. One way taxpayers may respond is by bunching at kink points in the tax schedule. We study this phenomenon using over 500 million federal individual income tax returns in the United States from 1996 to 2014. Though most kinks do not cause statistically discernible bunching, we present new evidence documenting the emergence and rapid rise of bunching at the second Earned Income Tax Credit
(EITC) kink and the Child Tax Credit refundability plateau, strong responses to the temporary Making Work Pay Tax Credit, and weak responses at three statutory kinks. Consistent with prior research, we also observe bunching at the first kink in the EITC schedule. The majority of bunchers are self-employed, though we find significant bunching among wage earners in recent years. Substantial bunching responses occur only at kinks that maximize tax credits, and the strongest response occurs at the unique point in the schedule that maximizes credits net of taxes owed.

The third chapter examines withdrawal patterns from traditional Individual Retirement Accounts (IRAs). In 2013, individuals age 60 or older held $3.9 trillion in wealth in these IRAs. Under current law, some fraction of these funds must be withdrawn each year beginning the year one turns 70.5 years of age, with the required fraction increasing in age. We study the effects of these Required Minimum Distribution (RMD) rules on the decumulation behavior of retirees using a 16-year panel of administrative tax data. Our data consist of a 5% random sample of individuals age 60 and older from 1999 to 2014: approximately 2.6 million individuals per year. This period encompasses a unique policy change that we exploit for identification: a one-year suspension of the RMD rules in 2009. Using a semiparametric technique we estimate the counterfactual density of IRA distributions in 2009 that would have prevailed if the rules had not been suspended. We estimate that at least 40% of the individuals subject to the RMD rules would take an IRA distribution less than their required minimum if they were unconstrained. In addition, we document an extensive margin effect among individuals newly subject to the rules.

**Index Words:** Taxation, Elasticity of Taxable Income, Cross-tax Elasticity, Bunching, Saving, Individual Retirement Account
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Much of this research embodies work undertaken by a staff member of the Joint Committee on Taxation, but as members of both parties and both houses of Congress comprise the Joint Committee on Taxation, this work should not be construed to represent the position of any member of the Committee. In particular, most of the data used in this dissertation were accessed as part of my employment at the Joint
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Chapter 1

All Income Is Not Created Equal: Cross-Tax Elasticity Estimates in the United States

1.1 Introduction

Many households in the United States face an effective marginal tax rate on long-term capital gains that is over 20 percentage points lower than the effective marginal tax rate applicable to their next dollar of wage income. Differential tax rates alter the relative after-tax return between different income earning activities, and likely induce individuals to change their patterns of saving, investment, or labor supply. In this paper, I estimate the extent to which individuals respond to this differential.

The deadweight loss or social cost associated with income taxation is generally an increasing function of taxpayer responsiveness. Estimates of the size and magnitude of taxpayer responses are necessary for estimating these costs and any tax revenue consequences of income tax changes. Understanding the nature of the response is important as well. Working fewer hours in response to a tax increase has different welfare and revenue implications than deciding to report less income. Similarly, shifting income earning activities between income types has different consequences than adjusting only one type. If income flows from one type of income to another in response to a tax increase the social cost of taxation is mitigated (Piketty et al., 2014).

Tax rate differentials might drive income responses in several ways. Fundamentally, decisions to work and save are generally not made in isolation. Both of these decisions
depend on the after-tax return to working and saving, which are themselves functions of the tax rates on both activities. For example, a reduction in long-term capital gains rates might increase the present discounted value of a retiree’s savings, causing them to retire early. Portfolio composition is also affected by tax differentials, as savings could generate ordinary income (e.g. interest from savings accounts) or long-term capital gains (e.g. returns realized from stock sales). Additionally, investment financing by firms or individuals is likely a function of tax differentials.

Surprisingly, microeconomic evidence of individual income responses to tax rate changes across income types in the United States is limited. Most work estimates the responsiveness of ordinary income to ordinary income tax rates, or capital gains to capital gains tax rates. Many consider inter-temporal responses within an income type, but few consider cross-income responses to changes in tax rates.

I analyze these issues using a large panel of non-public U.S. federal income tax returns spanning 1997 to 2007. This time period includes two major federal tax reforms – the Economic Growth and Tax Relief Reconciliation Act of 2001 (EGTRRA) and the Jobs and Growth Tax Relief Reconciliation Act of 2003 (JGTRRA) – as well as several smaller federal and state level reforms. These reforms generate cross-sectional and time-series variation in marginal tax rates used to identify elasticity estimates.

I focus on the degree to which ordinary income and long-term capital gains income are substitutable in the United States. I choose these types because the difference between long-term capital gains tax rates and ordinary income tax rates are large and salient, but in principle cross-tax effects could exist between any two tax bases with different tax rates. Responses to tax rates applied to different types of income are referred to as “cross-tax” responses, and are analogous to “cross-price” elasticities.
in a demand system. Responses of a given income type to changes in its own tax rate are referred to as “own-tax” responses.

I estimate cross-tax responses separately for both types of income: the effect of long-term capital gains taxes on ordinary income, and the effect of ordinary income tax rates on long-term capital gains realizations.\(^1\) I find significant ordinary income cross-tax effects on capital gains, and find slightly weaker evidence of ordinary income responses to changes in capital gains tax rates.\(^2\) Both sets of results are sensitive to specification decisions. In particular, statistically significant cross-tax effects in the capital gains setting vary depending on whether I consider one year or multi-year responses to tax rates. In the ordinary income setting, choice of year differences affect results.

The own-tax elasticity estimates for each income type are also interesting. Notably, estimates of ordinary income responses to ordinary income tax rate changes elicited by the Bush Tax Cuts are not discernible from zero in the standard framework abstracting away from cross-tax effects effects. This is inconsistent with other papers estimating elasticities using EGTRRA and JGTRRA. These papers suggest a 10% increase in the net-of-tax rate on ordinary income is associated with a 3 or 4% increase in ordinary income (Auten et al. (2008); Heim (2009); Singleton (2011)). Similarly, after implementing a series of econometric improvements following Weber (2014b) and Weber (2014a) I still fail to reject that ordinary income did not respond to changes in ordinary income tax rates associated with EGTRRA or JGTRRA. Including the net-of-tax rate on long-term capital gains produces some evidence suggestive of own-tax

\(^1\)While I include “ordinary” dividends in my definition of ordinary income, capital gains realizations do not include “qualified” dividends created as part of JGTRRA. See Chetty and Saez (2005) or Kawano (2014) for firm and individual responses to the dividend tax cut.

\(^2\)Kleven and Schultz (2014) estimate cross-tax elasticities in Denmark, and find the effect of labor income taxes has an effect on gross capital income. They also find labor income is not responsive to capital income taxes.
ordinary income responses, though the results are sensitive to such an extent that I
do not have a preferred estimate.

My preferred estimate of persistent long-term capital gains realizations responses
to capital gains taxes is similar to existing estimates in this time period, and is
statistically significantly different from zero: -0.90. However, the transitory elasticity
– arguably much less important than the persistent elasticity – is indistinguishable
from zero. My transitory elasticity estimate differs from Dowd et al. (2015), and likely
stems from my using one year less data.

The results of this paper suggest cross-tax responses between long-term capital
gains and ordinary income bases should be taken into account when evaluating pro-
posed changes to marginal income tax rates. Further, they suggest conventional wel-
fare and revenue analyses, which assume zero cross-tax elasticities, may be misleading.
Given the wide range of point estimates – including some that are statistically indis-
tinguishable from zero – I do not have a preferred point estimate, but the consistency
of the direction of the effect (suggesting the two income types are substitutes) is
strong and robust to specification decisions.

1.2 Review of Existing Work Estimating Taxable Income Elasticities

Most research on the elasticity of taxable income uses tax reforms as quasi-natural
experiments to estimate how individuals’ taxable income responds to changes in their
marginal tax rates. Marginal tax rate changes at the state and federal levels vary
across tax units depending on their household composition, income level, income
composition, and state of residence. This cross sectional variation in the effect of

\[ \text{Dowd et al. (2015) find a persistent long-term capital gains elasticity of } -0.79, \text{ which}
\] suggests a 10% increase in capital gains taxes is associated with a reduction in capital gains
realizations of roughly 8%.}
tax reforms allows for identification of a continuous treatment equation. Researchers mostly use samples of individual income tax returns to measure taxable income and an individual and state-of-residence specific marginal tax rate calculator to estimate a household’s state and federal marginal tax rates.\textsuperscript{4} The endogeneity that arises naturally through the mechanical relationship between income and marginal income tax rates is addressed using instrumental variables, which vary depending on the type of income in question.\textsuperscript{5}

Two separate bodies of work estimate taxable income elasticities in the United States. One estimates the responsiveness of ordinary income, which is essentially total or taxable income less capital gains, and the other focuses on long-term capital gains realizations, which are the realized nominal appreciation from the sale of an asset held at least one year. These two literatures largely fail to interact with one another. The ordinary income literature assumes short and long-term capital gains do not exist. The long-term capital gains literature assumes (a modified form of) ordinary income is exogenous. Both implicitly assume responses to tax rates on other types of income are zero. I review these two literatures briefly.

1.2.1 ORDINARY INCOME

An extensive and active body of work estimates own-tax ordinary income elasticities in the general style described in the preceding two paragraphs (Feldstein (1995); Auten and Carroll (1999); Gruber and Saez (2002); Kopczuk (2005); Giertz (2007); Auten et al. (2008); Heim (2009); Giertz (2010); Singleton (2011); Chetty (2012); Weber


\textsuperscript{5}A more recent body of work estimates tax elasticities by examining the degree to which taxpayers bunch at kink points. See Saez (2010) or Mortenson and Whitten (2016) for a U.S. study, Bastani and Selin (2014) for Sweden, Chetty et al. (2011) or Le Maire and Schjerning (2013) for Denmark, or Kleven and Waseem (2013) for Pakistan.
Saez et al. (2012) review the literature, and conclude the best estimates of a “long-run” elasticity of taxable ordinary income range from 0.12 to 0.40 in the United States. An elasticity at the top of this range, 0.40, suggests that taxable ordinary income will increase by 4 percent in response to a 10 percent decrease in the net-of-tax rate \((1 - \tau)\).

My paper is not the first to use the “Bush Tax Cuts” (i.e. EGTRRA and JGTRRA) as identifying variation: Auten et al. (2008), Heim (2009), and Singleton (2011) use them to estimate ordinary own-tax elasticities. Their estimates range from 0.2 to 0.7, with most estimates around 0.4.\(^6\) Each paper uses different panels containing individual earnings and examines slightly different combinations of years, and Singleton employs a different empirical specification than most previous studies.

However, recent work by Caroline Weber argues that most ordinary income tax elasticity papers use endogenous instruments. Weber estimates taxable ordinary income own-tax elasticities surrounding the Tax Reform Act of 1986. Replicating the seminal work in this literature, Gruber and Saez (2002), Weber finds that elasticity estimates increase from 0.3 to 0.9 when using the approximately exogenous instruments. Auten and Kawano (2011) apply Weber’s instruments to the Tax Reform Act of 1993. My paper represents the first application of these instruments to the Bush Tax Cuts.

1.2.2 Long-term Capital Gains Income

A much smaller body of work in the past twenty years estimates own-tax elasticities of realized long-term capital gains (Burman and Randolph (1994); Auerbach and Siegel (2000); Dowd et al. (2015)). The empirical specification in this literature –

\(^6\)See Heim and Mortenson (2016) for a corrected version of Heim’s results, wherein the elasticity estimates are indistinguishable from zero.
developed by Burman and Randolph (1994) – is a Tobit style sample selection model and reflects two key differences from ordinary income. First, capital gains realizations are further removed from a Haig-Simons definition of income than most elements of ordinary income. In particular, accruals in capital assets are treated as income under Haig-Simons, while realizations of nominal gains (generated from the sale of a capital asset held more than one year) are taxable income in the United States. Second, most households do have net positive long-term capital gains realizations in the United States in a given year.

Dowd et al. is the only study to estimate capital gains tax elasticities using the 2001 and 2003 reforms. Their preferred long-run estimate is -0.79, larger (in absolute terms) than that estimated by Burman and Randolph using the 1981 tax reform (-0.19), but smaller than that of Auerbach and Siegel using the 1986 and 1993 tax reforms (-1.72).\footnote{The expected sign on the elasticity in the capital gains setting is negative because the elasticity is calculated with respect to the tax rate, \( \tau \), as opposed to the net-of-tax rate used in the ordinary income setting, \( 1 - \tau \).} Transitory elasticity estimates are much larger, and vary to an even greater degree (ranging from -1.2 to -6.4). Taken together, however, it seems capital gains realizations are much more responsive to changes in its own tax rate than ordinary income realizations. This conforms with theoretical predictions, to the extent capital is more mobile than labor income (the largest component of ordinary income) and because capital gains realizations are taxed, as opposed to accrued capital gains. Realizations can be timed with taxes and asset price fluctuations in mind.

1.2.3 CROSS-TAX ELASTICITIES

Two papers estimate cross-tax elasticities between capital income and labor income, but both do so with significant qualifications. Kleven and Schultz (2014) utilize administrative and tax information on the population of Denmark between 1980 and 2005 to
estimate own-tax and cross-tax elasticities of labor income and capital income. They estimate cross-tax elasticities between these types of income, but only for individuals with negative capital income. They find that cross-tax elasticities between these two income types are small and negative. This suggests that capital and labor income are substitutes in the Danish tax system for this sub-population, and that at least some taxpayers respond to changes in marginal tax rates across income types.

Auten and Kawano (2011) investigate an array of taxable income responses to the Omnibus Budget Reconciliation Act of 1993 (OBRA). OBRA increased ordinary income marginal tax rates, but did not change long-term capital gains rates. Auten and Kawano have one specification in which long-term capital gains realizations are the dependent variable and ordinary income tax rates are included as an independent variable (instrumental variables following Weber (2014b) are used). They find that long-term capital gains increase in response to the increase in ordinary income tax rates, but note that they do not address the sample selection issues associated with estimating capital gains tax elasticities.8

Cross-tax responses create “fiscal externalities.” Saez et al. (2012) define a fiscal externality as “a change in the present value of tax revenue that occurs in any tax base \( z' \) other than \( z \) due to the behavioral response of private agents to the tax change in the initial base \( z \)” (p. 10). A tax base is defined as taxable income of a given type in a given time period. When tax bases have different tax rates, individuals have an incentive to shift income – whether through accounting tricks or re-allocation of resources – to lower taxed bases.9

8“Sample selection” issues refer to the large amount of zeros in the dependent variable. That is, most tax units do not realize long-term capital gains in a given year. However, presumably many of these tax units also do not have unrealized long-term capital gains.

9Fiscal externalities have been investigated in other contexts, most notably the shift from corporate income to pass-through entity income in response to the Tax Reform Act of 1986.
Given preferential (lower) long-term capital gains tax rates, this incentive exists between ordinary income and long-term capital gains in the United States. Saez et al. agree, arguing that the differential between long-term capital gains and ordinary income “matters and should ideally be controlled for in analyses of how the tax rate on ordinary income affects the reported amount of ordinary income” (p. 32). This paper takes some of the first steps toward achieving that ideal.

1.3 Theoretical Motivation

The reduced form estimation equation for taxable income elasticities falls out of a standard, static theoretic framework for income earning behavior. Following Kleven and Schultz (2014), individuals maximize utility by making consumption \( c \) and income earning \( z \) decisions with a composite consumption good and \( n \) income types, given individual characteristics \( x \) and a tax regime:

\[
\max_{c,z} u(c, z, x) \quad \text{(1.1)}
\]

\[
c = \sum_{j=1}^{n} z_j - T(z) = \sum_{j=1}^{n} (1 - \tau^j)z^j + y \quad \text{(1.2)}
\]

\[
y \equiv \sum_{j=1}^{n} \tau^j z^j - T(z)
\]

In this framework each individual income choice \( z^j \) is the result of some underlying trade-offs, such as a trade-off between supplying labor and consuming leisure or trade-off between earning different types of income. The individual has claim to after-tax income, which is the difference between the sum of each income type \( z^j \) and total tax liability \( T(.) \). After-tax income can be rearranged to be a function of virtual income \( y \) and the marginal net-of-tax return to each type of income. The optimal choice of \( z \) is a function of the tax rates on all other types of income, and virtual income \( y \):

\[
z^j = z^j(1 - \tau^1, \ldots, 1 - \tau^n, y, x) \quad \text{(1.3)}
\]
Here I extend the derivation in Gruber and Saez (2002), allowing for multiple income types. A total differentiation of equation 1.3 produces:

\[ dz^j = \frac{\partial z^j}{\partial (1 - \tau^j)} d(1 - \tau^j) + \sum_{k \neq j}^{n} \frac{\partial z^j}{\partial (1 - \tau^k)} d(1 - \tau^k) + \frac{\partial z^j}{\partial y} dy. \]  

(1.4)

The uncompensated cross-tax elasticity of income type \( j \), with respect to the tax rate on income type \( k \), takes the form

\[ \xi^{jk} \equiv \frac{\partial z^j}{\partial (1 - \tau^k)} \frac{(1 - \tau^k)}{z^j} \]

and the income elasticity is\(^{10}\)

\[ \eta^j \equiv \frac{\partial z^j}{\partial y} \frac{y}{z^j}. \]

Substituting these into equation 1.4 produces

\[ dz^j = \xi^{jj} \frac{d(1 - \tau^j)}{1 - \tau^j} z^j + \sum_{k \neq j}^{n} \xi^{jk} \frac{d(1 - \tau^k)}{1 - \tau^k} z^j + \eta^j \frac{z^j}{y} dy. \]

(1.5)

In order to get this into an estimable form, I divide both sides by \( z^j \)

\[ \frac{dz^j}{z^j} = \xi^{jj} \frac{d(1 - \tau^j)}{1 - \tau^j} + \sum_{k \neq j}^{n} \xi^{jk} \frac{d(1 - \tau^k)}{1 - \tau^k} + \eta^j \frac{dy}{y}, \]

and substitute the “change over level” terms for their approximate natural logarithmic approximations

\[ \ln \left( \frac{z^j_{t+s}}{z^j_t} \right) = \xi^{jj} \ln \left( \frac{1 - \tau^j_{t+s}}{1 - \tau^j_t} \right) + \sum_{k \neq j}^{n} \xi^{jk} \ln \left( \frac{1 - \tau^k_{t+s}}{1 - \tau^k_t} \right) + \eta^j \ln \left( \frac{y_{t+s}}{y_t} \right). \]  

(1.6)

The term \( \xi^{jj} \) is the uncompensated own-tax elasticity for income type \( j \), \( \eta^j \) is the income elasticity, and \( s \) is some number of periods after time \( t \). We expect the uncompensated own-tax elasticity to be positive, as the “price” variable is 1 minus the tax

\(^{10}\)This construction of the income elasticity follows Kleven and Schultz and differs from Gruber and Saez, who define an income effect parameter in terms of the change in after-tax income. In the presence of multiple marginal tax rates – resulting in a kinked budget constraint – after-tax income is not the correct measure of an income effect, as it ultimately provides information on the average tax rate, not the marginal rate.
rate, and the income elasticity is negative assuming $z$ are inferior goods. The compensated elasticity is a function of these two parameters and is ambiguously signed. Equation 1.6 is the basis of my estimation equation used in the ordinary income setting. The capital gains estimation framework modifies this substantially, for reasons alluded to in Section 1.2.2 (e.g. the dependent variable is mostly zeros).

1.3.1 **CROSS-TAX ELASTICITIES**

The simple theoretical model used in the derivation above assumes individuals evaluate the after-tax return to different income earning activities, and might respond to tax rate changes through a number of channels. These channels include altering income earning behavior in income types that did not experience a tax rate change. Such responses might involve actual reallocation of resources between different economic activities (i.e. a “real” economic response). Individuals may alter the amount of labor they supply in response to expected after-tax returns to savings vehicles eligible for long-term capital gains rates. Similarly, individuals may save more and ultimately realize more long-term capital gains in response to ordinary income tax changes.

Households also might respond through tax avoidance. With only one income type, the returns to avoidance or evasion are increasing functions of tax rates. With multiple income types, the differential between income types is also important. Examples of avoidance activities between ordinary income and long-term capital gains include investing income earned by partnerships or Sub-chapter S corporations – which is passed-through and taxed at the individual level – in assets generating long-term capital gains. Another opportunity is available to those with home mortgages, whose interest are deductible for itemizers. Tax units can choose to invest in assets

\[11\] Responses that are non-compliant with tax law are also a possibility, though we might expect this would be reflected more in own-tax responses than cross-tax responses.
generating long-term capital gains as opposed to paying down their mortgage debt. Others include timing responses, such as delaying the realization of a short-term capital gain until it qualifies for preferential long-term rates. Higher capital gains tax rates might also increase contributions to savings vehicles taxed at ordinary income rates, such as traditional individual retirement arrangements (IRAs).

1.4 Data Sources and the U.S. Tax System

The primary source of data used in this paper is a non-public panel of federal income tax returns produced by the Statistics of Income (SOI) division of the Treasury Department. The panel is based on an income-stratified sample of tax filing units in 1999, and high income individuals are over-sampled (i.e. they are sampled at a higher rate). Each of the roughly 85,000 tax units is assigned a sample weight based on its strata, and in 1999 the sample represents a population of roughly 123 million tax returns. I extend the data back to 1997 by selecting returns for the primary filer in 1997 and 1998 with the same marital status as in 1999.

The resulting sample contains roughly 900,000 observations spanning tax years 1997 to 2007 prior to any sample restrictions. The panel includes information on ordinary and capital gains income items, as well as credits, deductions, exemptions, and any available demographic information. Weber and Bryant (2005) provide a detailed description of the panel, which has been updated annually since 2003.

Tax data do not contain any direct information on asset holdings, though they do include information on income or deductions related to capital asset holdings. Capital gains realizations, interest income, mortgage interest deductions, and dividend income all give an indication of the type and amount of assets held by a tax unit. I use an algorithm produced by Rob McClelland to impute unrealized capital gains levels.

1.4.1 Income Definitions and Marginal Tax Rates

I use two definitions of income in the ordinary income portion of the paper. The first, broad income, is defined as total income from the Form 1040, less capital gains and gross Social Security income, plus tax exempt interest income. The second, taxable income, is defined as taxable income from the Form 1040, less capital gains and gross Social Security income.\textsuperscript{12} Total income and taxable income differ primarily in that adjustments and deductions are excluded from taxable income, but not from total income. I follow most of the other papers in this literature by constructing a “constant law” measure of income. This is accomplished by including deductions in my measure of taxable income that were created or expanded during the sample period.

There are several important characteristics of taxable capital gains in the United States. First, capital gains are taxed upon realization, not accrual. Second, capital gains are generally placed into two bins: short-term capital gains (gains from the sale of an asset held less than one year) and long-term capital gains. Both are included in taxable income on the Form 1040, but long-term capital gains are separated from taxable income when calculating tax liability. This means that short-term gains are subject to the ordinary income marginal tax rate schedule, and long-term gains are generally subject to lower, preferential rates. Third, capital losses can only be deducted against ordinary income after all short-term and long-term capital gains have been exhausted, and only then at a maximum value of $3,000. Finally, net capital losses in excess of $3,000 can be carried forward and applied against future capital gains and

\textsuperscript{12}These definitions follow Heim (2009). Auten et al. (2008) define taxable income similarly, except they do not remove Social Security income.
future ordinary income, with a maximum annual deduction against ordinary income of $3,000, and an unlimited annual deduction when applied against capital gains.

An important part of any tax elasticity paper is estimating effective marginal tax rates. Effective rates often vary significantly from statutory rates – the rates actually written in law – because they take deductions, credits, phase-out regions for deductions and credits, income composition, and the alternative minimum tax into account. Estimating them requires a complicated Turbo-Tax-esque calculator at the state and federal levels, along with assumptions about the operative channel for responding to marginal tax rate changes. I follow Heim (2009) by assuming labor income is the operative channel of ordinary income response when labor income is the primary source of income, and assume business income is the operative channel when it is the primary source of income. The ordinary income tax rate includes payroll and state and federal income taxes. The state and federal marginal tax rate calculator I use is built and maintained by Jon Bakija (2009).

1.4.2 U.S. Federal Income Tax Rates

The motivation for this paper is the often substantial differential between effective long-term capital gains marginal tax rates and ordinary income marginal tax rates. Figure 1.1 presents the effective marginal tax rates on ordinary income (solid navy line) and long-term capital gains (dashed red line) using simulated data for a married household with one dependent living in a state without state-level individual income taxes in 2007. In all of these figures, marginal tax rates are censored at zero, and are calculated assuming no income of any other type. For example, when considering the navy line, $100,000 refers to $100,000 of ordinary income (in this case, wage income)
and $0 of capital gains. Similarly, when considering the dashed red line line, $100,000 refers to $100,000 of long-term capital gains and $0 of ordinary income.  

Two aspects of this graph are striking. First, marginal taxes of both types are generally increasing, but are definitely non-monotonic functions of income. Phase-in and phase-out regions of credits and deductions, the alternative minimum tax, exemption phase-outs, and statutory marginal tax rate kinks cause effective rates to jump and fall. Second, tax rates on long-term capital gains are much lower than ordinary income rates for all but very low income levels (because the Child Tax Credit, for instance, is a function of “earned income” only). Figure 1.2 displays the differential between ordinary income rates and long-term capital gains rates, which ranges from around 11% to 21%, and exhibits substantial variation by income level.

1.4.3 The “Bush Tax Cuts”: EGTRRA and JGTRRA

These data span two major federal tax reforms – the Economic Growth and Tax Relief Reconciliation Act of 2001 (EGTRRA) and the Jobs and Growth Tax Relief Reconciliation Act of 2003 (JGTRRA) – along with several state level income tax reforms.\textsuperscript{14} EGTRRA established a gradually decreasing path for marginal tax rates over time. JGTRRA sped the process up, fully enacting the tax cuts in 2003. See Auten et al. (2008) for a detailed summary of the federal reforms as they relate to estimating elasticities of taxable ordinary income.

The reforms were large and expensive relative to the existing policy baseline, and there are several aspects that are important to keep in mind. First, between

\textsuperscript{13}Without censoring at zero the ordinary rates would be significantly negative at small income levels due to subsidies – ranging from 7.65 percent to 45 percent – found in the phase-in region of the Earned Income Tax Credit.

\textsuperscript{14}The Taxpayer Relief Act of 1997 is also part of the data, but these data are only used as instruments or control variables as my preferred specifications include instruments constructed from lagged income.
2001 and 2003, statutory federal tax rates decreased in every bracket except the 15 percent bracket, most by around 3 or 4 percentage points, and a new 10 percent ordinary income bracket was created. Second, in 2003 capital gains rates were cut by 5 percent in both long-term capital gains brackets. Also, dividends earned from qualifying assets were made eligible for preferential long-term rates. Third, marriage penalties were reduced – essentially the tax brackets for married individuals were lengthened – and the child tax credit was gradually made more generous. Finally, the definition of taxable income was not seriously altered, with one exception: dividends received from assets qualifying for long-term capital gains rates (if sold) were subject to long-term capital gains rates, while “ordinary” dividends were subject to ordinary income rates.\footnote{Heim (2009) and Auten, Carroll, and Gee (2008) do not remove dividends from their definitions of income. I follow their lead in my base case, but present robustness checks to excluding all dividends (ordinary and qualifying).}

Figure 1.3 presents the effective ordinary income and long-term capital gains tax rates faced by a married tax unit with one dependent living in a state with no income taxes in 2000 and 2005. The thick navy and thick dashed red lines represent the effective marginal tax rates in 2000 for ordinary income and long-term capital gains, respectively. The thinner solid navy line and thinner dashed line represent the effective marginal tax rates in 2005 for ordinary income and long-term capital gains rates, respectively. The tax cuts cause the thinner lines – representing the 2005 effective tax rates – to fall below the solid lines for most income amounts in this range. This is highlighted in Figure 1.4, which displays the change in effective marginal tax rates for each income type directly. The size of the change varies with income, but with some exceptions the rates were lowered for most income levels.

The differential between long-term capital gains tax rates and ordinary income tax rates also changed, as shown in Figure 1.5. Cross-sectional variation in this differential
is important for estimating cross-tax responses. If this differential was constant the treatment would be the same for all observations and identifying a cross-tax responses in this style would be impossible. A better set of performs would ideally involve directional changes for the two income types, in addition to changes in magnitude: for instance, capital gains rates increase while ordinary income rates decrease. Lacking changes in both rates, it might also be instructive to revisit past reforms which altered rates on one type of income but did not alter rates on the other.

1.5 Ordinary Income Tax Elasticities

This section covers the estimation framework used to estimate own-tax and cross-tax ordinary income elasticities. I review the standard approach, and discuss how my preferred specification differs in light of Weber (2014a) and Weber (2014b), and the consideration of cross-tax responses.

1.5.1 Standard Ordinary Income Estimation Framework

What I will refer to as the “standard framework” for estimating ordinary income tax elasticities follows Gruber and Saez (2002) and Kopczuk (2005). It is a version of equation eq: log est limited to one income type (ordinary income) and some combination of base year and one period lagged income controls \((h(z_i))\) to control for mean reversion or different income growth rates.

\[
\ln \left( \frac{z_{t+s}}{z_t} \right) = \xi^u \ln \left( \frac{1 - \tau_{t+s}}{1 - \tau_t} \right) + \eta \ln \left( \frac{y_{t+s}}{y_t} \right).
\]

Observations are at the tax unit level level, \(i\), in year \(t\). Two or three year differences are used (i.e. \(s = 2\) or \(s = 3\)), which address individual fixed effects. I also include a vector of observable individual characteristics (both time-variant and time-invariant),
\( X_{it} \), and year fixed effects, \( \alpha_t \). The residual is \( \ln(\nu_{it}) \).

\[
\Delta \ln(z_{it}) = \xi^a \Delta \ln(1 - \tau_{it}) + \eta \Delta \ln(y_{it}) + X'_{it} \beta + \alpha_t + h(z_{it}) + \Delta \ln(\nu_{it}). \tag{1.7}
\]

The coefficient on the log net-of-tax-rate, \( \xi^a \), is the uncompensated elasticity of ordinary taxable income and the coefficient on virtual income, \( \eta \), is the income elasticity.

Marginal tax rates \( \tau \) are functions of taxable income in a progressive tax system, which means the net-of-tax rate is an endogenous variable. As a result, ordinary least squares estimation (OLS) of the coefficients in this equation would have a negative sign, suggesting higher tax rates cause higher income.

Two-stage least squares estimation is used to address the endogeneity problem, with simulated instruments constructed using “predicted” net-of-tax rates holding income constant at base year levels.\(^{16}\) The term \( \tau_{it}^{P|Z_{it}} \) represents the predicted or simulated marginal tax rate in year \( t \) for individual \( i \), with income held constant at the base year level used to estimate the marginal tax rates.

\[
\Delta \ln(1 - \tau_{it}^{P|Z_{it}}) = \ln(1 - \tau_{it+s}^{P|Z_{it}}) - \ln(1 - \tau_{it}^{P|Z_{it}})
\]

1.5.2 Baseline Estimates and Modifications

To establish baseline results I replicate Heim (2009). Heim follows the standard framework, but also abstracts away from income effects (i.e. assumes \( \eta = 0 \)).\(^{17}\) Heim uses the same set of data that I use here, and also uses the same marginal tax rate calculator (Bakija, 2009). Heim’s preferred specification – which includes base year income weights – produces own-tax ordinary income elasticity estimates of 0.4, but Heim and

\(^{16}\) The base year refers to the earlier year in a difference equation. That is, if using 3 year lagged differences the base year is \( t \) and the forward year is \( t + 3 \).

\(^{17}\) Gruber and Saez (2002) estimate income effects, but many papers do not.
Mortenson (2016) reproduce these results with a correction to the definition of taxable income and find estimates indistinguishable from zero. These are my baseline results, but I make a series of changes to the standard estimation framework, mostly following Weber (2014a) and Weber (2014b).

**INSTRUMENT SELECTION**

The two necessary properties of a valid instrument $z_{it}$ are relevance and exogeneity. Relevance refers to the property that the instrument is sufficiently correlated with the endogenous variable ($\text{cov} [\Delta z_{it}, \Delta \ln(1 - \tau_{it})|X_{it}] \neq 0$). Exogeneity requires that the instrument is uncorrelated with the error term, conditional on the other covariates ($\text{cov} [\Delta z_{it}, \Delta \ln(\nu_{it})|X_{it}] = 0$).

Instruments constructed following Auten and Carroll (1999) or Gruber and Saez (2002) typically satisfy empirical tests of relevance (e.g. F-test statistics on the first stage regression results are large), but are not exogenous (Weber, 2014b). This is because shocks to base year income ($\ln(\nu_{it})$), which would directly influence the predicted marginal tax rates, are also found in the error term of the estimation equation ($\Delta \ln(\nu_{it})$). Weber proposes a set of approximately exogenous simulated instruments, where predicted net-of-tax rates are estimated holding income constant at an inflation-adjusted level some $n$ years prior to the base year income:

$$
\Delta \ln(1 - \tau_{it}^{P|Z_{it-n}}) = \ln(1 - \tau_{it+3}^{P|Z_{it-n}}) - \ln(1 - \tau_{it}^{P|Z_{it-n}})
$$

(1.8)

In Weber’s specification income shocks can be serially correlated and the instruments will remain approximately exogenous so long as the number of lags ($n$) is sufficiently large. The bias remaining from serially correlated transitory income shocks

---

18Heim (2009) includes short-term and long-term capital gains in his definition of income by mistake. See Heim and Mortenson (2016) for a more detailed description of the replication.
is decreasing in the number of periods before the base year.\textsuperscript{19} A standard F-test of the first-stage estimates can be used to ensure instruments are sufficiently relevant, and Weber uses a difference-in-Sargan test to estimate whether instruments lagged \( n \) periods are exogenous (assuming instruments lagged \( n + 1 \) or \( n + 2 \) periods are exogenous).

My preferred instruments for ordinary income and capital gains tax rates when estimating elasticities in the ordinary income framework (i.e. the dependent variable is the log change in ordinary income) are constructed using two and three period lagged income, so long as difference-in-Sargan tests are satisfied. The variation in marginal tax rates over time and within a given year associated with both state and federal reforms – as well as the variation provided by the deductibility against federal taxable income of state and local income taxes – enters through these instruments and is used to identify elasticity estimates.

\textbf{Virtual Income}

Constructing a good approximation of virtual income, \( y_{it} \), is challenging given multiple income types and the limited deductibility between capital income and ordinary income. I define virtual income in year \( t \) for individual \( i \) to be the sum of wage income times the wage income marginal tax rate \( z_{it}^w \tau_{it}^w \), business income times its tax rate \( z_{it}^b \tau_{it}^b \), gross taxable income less wage, business, and capital gains income times the interest income tax rate \( z_{it}^x \tau_{it}^x \), the maximum of net long-term capital gains and \(-\$3,000 \) times its tax rate, and the maximum of net short-term capital gains and \(-\$3,000 \) times its tax rate; less the sum of federal (\( T^F(z_{it}) \)), state (\( T^S(z_{it}) \)), and payroll

\textsuperscript{19}Weber (2014b) finds that using approximately exogenous instruments constructed using lagged income increases elasticity estimates surrounding the 1986 Tax Reform Act from 0.3 to 0.9.
taxes $(TP(z_{it}^w))$.

$$y_{it} = z_{it}^w \tau_{it} + z_{it}^b \tau_{it}^b + z_{it}^f \tau_{it}^f + \max(z_{it}^c, -3,000) \tau_{it}^c + \max(z_{it}^k, -3,000) \tau_{it}^k -(TF(z_{it}) + TS(z_{it}) + TP(z_{it}^w))$$

As virtual income is a function of marginal tax rates, it is also endogenous. Instruments for virtual income are constructed by simulating the tax rates used in the equation above using lagged base year income. Similarly, the income amounts are adjusted for inflation to match the price level in the simulated year.\(^2\)

**Base Year Income Controls**

I include a function of income as a control $(h(z))$, which is standard in the literature. Income controls are meant to address two problems. First, transitory income shocks might dissipate over time, generating mean reversion. If this is the case, individuals with high (low) income in the base year might see incomes fall (rise) in the forward year, independent of tax reforms. This could bias estimates if the change in tax rates varies with income. Second, individuals at different sections of the income distribution might have different income growth rates, again, independently of tax reforms. Controlling for varying growth rates at different levels of income will help to mitigate both biases. In my preferred specification, $h(z)$ takes the form of a 10 piece spline in income lagged two and three periods. Note that splines constructed using base year income - the standard approach in this literature - are endogenous (Weber, 2014b).

\(^2\)Because effective marginal tax rates are non-monotonic functions of taxable income (e.g. see 1.1) virtual income is negative for some individuals. This results in these observations being dropped, as virtual income enters into the regression equation in logs. The exact number depends on the specification, but comparing Table 1.2 and Table 1.3 suggests between 40,000 and 60,000 observations are dropped when virtual income is included as an endogenous regressor.
Treatment Definition

Weber makes a different point in another paper (Weber, 2014a), namely that the definition of “treatment” used in the ordinary income literature – the log change in the actual tax rate faced by a tax unit – is measured with error. Weber (2014a) terms this as “treatment mis-measurement.” In particular, individuals might respond across kinks in the effective marginal tax rate schedule for a number of reasons, including optimization frictions and income volatility. Weber demonstrates that a causal intent-to-treat effect (ITT) can be estimated under the assumption that the instruments used to address the endogeneity of the treatment are independent of secular income trends and transitory income shocks.

Estimating a causal average treatment effect requires the additional assumption that instruments are independent of any incentives to cross kinks. Given the number of “brackets” in the effective rate schedule (e.g. see 1.1) and the complexity involved in estimating effective marginal rates, this is a valid concern. The practical difference between an estimable average treatment effect in this setting – what Weber terms a “fixed bracket average treatment effect” (FBATE) – and an ITT effect is in the definition of treatment. An FBATE uses the log change in the actual tax rate faced by a tax unit, while an ITT uses the predicted log change in tax rates holding base year income constant. I present both FBATE and ITT estimates, though my preferred specification is an ITT estimate. I also use analogous definitions of treatment for virtual income.

Preferred Specification

Equation 1.9 represents my base specification in the ordinary income setting. It includes the log of net ordinary income ($\ln(1 - \tau_{oi})$) and long-term capital gains
(\ln(1 - \tau^c_{it})) tax rates as endogenous regressors. The log change in virtual income
(\Delta \ln(y_{it})) is also endogenous. To address this endogeneity I use an analogously con-
structed set of instruments for each variable, namely predicted changes using multiple
years of lagged income. In my preferred specification all three endogenous variables
enter as predicted changes holding income constant in the base year. The estimates are
weighted by the probability of being sampled, and no income weights are applied.\(^{21}\)

\[
\Delta \ln(z^o_{it}) = \xi^{oo} \Delta \ln(1-\tau^o_{it}) + \xi^{oc} \Delta \ln(1-\tau^c_{it}) + \eta \Delta \ln(y_{it}) + X_{it}'\beta + h(z)'\sigma + \Delta \ln(\nu_{it}) \tag{1.9}
\]

I make several restrictions to the sample, all of which follow the existing literature.
First, I drop observations whose marital status changes between the base year and
forward year, or any relevant lagged year used to construct instruments or base year
income controls. This is done to ensure that income changes are not largely the result
of changes in household structure. Second, I limit my estimation sample to those with
broad income in excess of $10,000 in the base year. In practice this is not a binding
constraint for most tax units who file tax returns. Third, I drop observations with
primary filers aged less than 25 or older than 100 in the base year, in an attempt
to reduce the influence of college or end-of-life decisions. Fourth, households without
valid zip codes are dropped, as state marginal tax rates are used. Finally, I drop
observations who died in a given tax year or have sample weights of zero.

Control variables include number of children, age, age-squared, and dummy vari-
ables for business income, itemizer status, and region. All regressions in this section
include year fixed effects. Errors are clustered at the tax unit level. The data used to
construct the dependent and independent variables (as opposed to the controls and

\(^{21}\)Weighting estimates using base year income is also problematic: shocks to base year
income are correlated with shocks to the dependent variable. A tax unit receiving a large
positive (negative) transitory income shock should expect the shock to dissipate in the
forward year, biasing estimates associated with tax decreases downward (upwards). This
has a net effect of biasing estimates towards zero.
lagged instruments) are limited to the years 2000 to 2004 to ensure similar data are used in all specifications. Table 1.1 displays the mean values and associated standard errors of dependent variables, independent variables, and marginal tax rates.

1.5.3 Implementing My Preferred Specification

Three features of the standard approach are almost certainly invalid and have the potential to bias estimates: instruments constructed using base year income, income controls constructed using base year income, and base year income weights. Instead, I construct instruments using lags of base year income; I construct income controls (10 piece splines) using income lagged two and three periods; and I opt not to use any income weights. I refer to this specification as “Heim’s modified specification.”

Three other specification decisions are more a matter of opinion, and Table 1.2 contains coefficient estimates meant to establish the sensitivity of results to these choices. First, Heim’s data cover the base years 2000, 2001, and 2002, as these were the most recent data available at the time of publication. I add base years 2003 and 2004. Second, Heim’s preferred specification uses three year differences; I try two year differences. I am motivated to make this change because the measurement error associated with the “treatment” variable – the change in tax rates between years – could be increasing in the number of years used for differencing. A two-year difference might allow the tax unit time to learn about the tax change, but is hopefully not so long that the household hasn’t changed to such a degree as to weaken the definition of treatment. Third, my preferred specification replaces the definition of treatment traditionally used in this literature – the actual, realized change in tax rates between year $t$ and year $t + 2$ – with the predicted change holding income constant in year $t$, capturing an ITT effect.
Table 1.2 presents coefficient estimates, with standard errors in parentheses, from the second stage of a two-stage least squares regression. The log change in ordinary income is the dependent variable, which means the coefficients associated with the net-of-tax rates, \( \Delta \ln(1 - \tau^o) \), can be interpreted as estimates of uncompensated own-tax elasticities of ordinary income. Note that the expected sign of the elasticity is positive, as the “price” variable is 1 minus the marginal tax rate. Higher marginal tax rates will cause the net-of-tax rate to decline, and we expect individuals to reduce income in response to higher tax rates, ceteris paribus.

I begin by testing the validity of instruments. In particular, I test how many lags are necessary to reject the null hypothesis of a difference-in-Sargan test of whether the instrument constructed using the most recent year’s income is exogenous. Each column in Table 1.2 contains a modified version of Heim’s specification. I substitute splines in base year income for splines in two-period and three-period lagged gross income income, and drop base year income weights in favor of sample weights. Three year differences are used, data years are 2000, 2001, and 2002, and the definition of treatment is the actual realized change in net-of-tax rates.

Column 1 uses instruments constructed using base year income. The coefficient estimate is 0.074, with approximately the same standard error. Column 2 uses instruments constructed using base year and two and three periods lagged income, allowing for a test of whether instruments constructed using base year income are exogenous (assuming other excluded instruments are exogenous). The p-value on the difference-in-Sargan test is 0.41, meaning I cannot reject that the instrument constructed using base year income is exogenous.\(^{22}\) The coefficient and standard errors are unchanged after including the two additional excluded instruments.

\(^{22}\)No difference-in-Sargan test is performed in Column 1 because only one excluded instrument is used.
Column 3 uses instruments constructed using 1 year, 2 year, and 3 year lagged income. The p-value is 0.51, again meaning that we cannot reject that simulated instruments constructed using one period lagged income is exogenous. The coefficient estimate is 0.21 – in the range of other elasticity estimates in this time period – but the standard error is 0.29. Column 4 uses instruments constructed using two year and three year lagged income. The p-value is 0.90. Again, the coefficient and standard error are approximately the same: 0.43 and 0.45, respectively.

Failing to reject that instruments constructed using base year income are exogenous is surprising given Weber’s empirical and analytical results. Weber demonstrates that instruments constructed from base year income are endogenous, and that instruments constructed using one period lagged income are also endogenous in the presence of moderately serially correlated income shocks. Ultimately, I remain convinced by Weber’s analytical results, and choose to use instruments constructed from income lagged two and three years prior to the base year.

Table 1.3 provides a sense of how my three changes to “Heim’s modified specification” – two year differences, additional years of data, and an alternate definition of treatment – affect own-tax elasticity estimates. Column 1 is identical to Column 4 in Table 1.2, and is Heim’s modified specification. Column 2 uses two year differences instead of three, holding the other decisions equal. Column 3 includes years 2003 and 2004, but is otherwise identical to Heim’s modified specification. Column 4 uses the intent-to-treat definition of treatment, but is again otherwise similar. Column 5 uses

---

23 First stage F-test statistics are reported in the table and do not suggest weak instruments are an issue here.
24 Of course, failing to reject a null is different than proving the null to be true.
25 I will continue to employ difference-in-Sargan tests in specifications with only one endogenous variable and at least two excluded instruments.
26 Instruments are constructed from income lagged 2 and 3 periods are used in all specifications in this table, and throughout the remainder of the ordinary income section unless otherwise noted.
the extra data and two year differences, but the standard definition of treatment. Column 6 uses the extra data and the intent-to-treat estimator, but three year differences. Column 7 uses two year differences and the intent-to-treat estimator, but data only from 2000, 2001, and 2002. Finally, Column 8 uses the extra data, two year differences, and the alternate definition of treatment. Ex ante, Column 8 is my preferred specification.

This table suggests own-tax ordinary income elasticity estimates in the style of Weber (2014a & 2014b) are indistinguishable from zero. The estimates have the correct sign in each specification, but are imprecise, with standard errors ranging from 0.25 to 0.45. Because of this, all of the point estimates in this table are consistent with other findings in this literature, but are also consistent with elasticities of zero.\textsuperscript{27}

Two of the specification decisions have clear patterns. Two year differences yield smaller estimates: the set of estimates using two year differences in columns 2, 5, 7, and 8 is strictly less than the set using three year differences in columns 1, 3, 4, and 6. This suggests tax units require several periods to respond, as opposed to only two. The ITT estimates in columns 4, 6, 7, and 8 have strictly smaller standard errors than the ATE estimates in columns 1, 2, 3, and 5. This is consistent with (Weber, 2014a), who finds that ITT estimates are more precise than ATE estimates. Finally, adding additional data seems to have a smaller effect than the other two choices: some estimates are smaller, some larger; some more precise, some less.

\subsection*{1.5.4 Ordinary Income Elasticity and Income Effect Estimates}

This section incorporates the possibility of cross-tax responses and income effects. I do not have strong priors regarding the estimates produced in my preferred specification.\footnote{The F tests of weak instruments and difference-in-Sargan tests do not suggest a problem in either dimension.}
Three papers estimate own-tax ordinary income elasticities using the Bush Tax Cuts, with estimates ranging from zero to 0.4 (Auten, Carroll, & Gee, 2008; Singleton, 2011; Heim & Mortenson, 2016). However, Heim and Mortenson and Auten, Carroll, and Gee use invalid instruments to address the endogeneity of marginal tax rates. Singleton uses a novel set of earnings data matched with Current Population Survey data, but focuses exclusively on married tax units near the kink point between 15 and 27 percent. Similarly, the only existing cross-tax estimates in the U.S. don’t account for potentially important sample selection issues, and the only estimates from outside the U.S. are from Denmark (and, again, the instruments used are likely invalid).

**INCORPORATING INCOME EFFECTS**

Table 1.4 is a recreation of Table 1.3, with the addition of the log change in virtual income as an endogenous regressor. The coefficient associated with this variable is an income elasticity, and is expected to have a negative sign. It mimics the form of the ordinary income tax rate, entering as the actual change in log virtual income in columns 1, 2, 3, and 5, and as an ITT in columns 4, 6, 7, and 8.\(^{28}\)

The results in Table 1.4 do not tell a nice story. First, none of the coefficients of interest are distinguishable from zero. Second, while all of the income effect point estimates have the expected sign (negative), three of the ordinary income point estimates have an unexpectedly negative sign. Further, the standard errors in Table 1.4 are strictly larger – in some cases much larger – than those in Table 1.3. This could be the result of fewer observations (many observations have negative virtual income\(^{28}\)

\(^{28}\)In specifications excluding income effects and cross-tax effects – such as those in Table 1.2 – I am able to test the exogeneity assumption for ordinary income instruments using a difference-in-Sargan. This test is not valid in the presence of multiple endogenous variables, and since all regressions reported here include at least two endogenous variables I do not perform the test.
and are dropped) or collinearity between the virtual income and ordinary income tax variables. These findings are consistent with a large degree of measurement error in the construction of virtual income, and argue against their inclusion in future specifications.

**Incorporating Cross-Tax Effects**

Table 1.5 is a recreation of Table 1.3, with the addition of the log change in long-term capital gains as an endogenous regressor. The coefficient associated with the capital gains tax rate is a cross-tax elasticity, and is expected to have a negative sign. It mimics the form of the ordinary income tax rate, entering as the actual change in log long-term marginal tax rates in columns 1, 2, 3, and 5, and as an ITT in columns 4, 6, 7, and 8.

Table 1.5 suggests ordinary income decisions are responding to long-term capital gains taxes in the expected direction. All of the coefficients associated with the cross-tax variables are negative, which indicates that higher long-term capital gains tax rates are associated with higher ordinary income realizations (remember that the variable is the log change in 1 minus the tax rate). Further, in all of the columns with three year differences (1, 3, 4, and 6) I can reject the null hypothesis of no cross-tax responses at a 5 percent significance level. The magnitudes of the statistically significant estimates range from perhaps implausibly large (-2.4) to reasonable (-0.77), and are suggestive of substantial cross-tax responses.

In all of the columns with three year differences (1, 3, 4, and 6) the ordinary income own-tax elasticities are distinguishable from zero, but also contain some perhaps implausibly large results. The estimates in columns 1 and 3 suggest increases in the net-of-tax rate of 10% (for example, if marginal tax rates change from 30% to 23%) are associated with increases in ordinary income of 13% or more. The estimates
in columns 4 and 6 – which are ITT effects – are more reasonable, with own-tax and cross-tax elasticities of around 0.8. This table again suggests that three year responses are more substantial than two and that ITT estimates are more precisely estimated.

Table 1.6 is a re-creation of Table 1.3, with the addition of the log change in virtual income and long-term capital gains rates as endogenous regressors. Once again, they mimic the form of the ordinary income tax rate. Recall that we expect the sign of the own-tax elasticity to be positive, the cross-tax elasticity to be negative, and the income elasticity to be negative. Unsurprisingly, these results are qualitatively a mix of those in Table 1.4 and Table 1.5. The cross-tax and virtual income elasticity estimates have the expected sign in each specification, and the cross-tax estimates produced using three year differences are large and statistically significant. The own-tax elasticities have the expected sign in all specifications except Column 2, though most of these estimates are statistically insignificant.

**Relevant Sub-Populations**

Of course, own-tax and cross-tax elasticities may be heterogeneous. Households vary in their asset holdings, income, and tax-system information sets. Also, while many tax units have positive (nominal) accrued capital gains in a given year, relatively few actually sell those assets in a given year (realizing taxable capital gains). With this in mind, Table 1.7 presents own-tax, cross-tax, and virtual income elasticities, with clustered standard errors in parentheses, for sub-populations (selected ex ante) that might be particularly responsive to own-tax or cross-tax changes. I use the same regression specification – three year differences with the full set of data and an ITT definition of treatment – to produce the coefficients estimated in this table.

The first two rows of Table 1.7 display estimated elasticities using base-year broad income floors of $50,000 or $100,000 (i.e. income in year $t$ must be at least $50,000).
Row 3 contains estimates performed on the population of individuals with non-zero short-term or long-term capital gains in either the base or forward year, and at least $10,000 of broad income in the base year. Row 4 is similar, only those with interest or dividend income are included. Row 5 limits the sample to those with pass-through income (i.e. income from partnerships or Sub-Chapter S-Corporations). Row 6 proxies for tax-payer knowledge by limiting the sample to those returns with a non-zero itemized deduction for “paid tax preparer.”

Itemizers with paid preparers are the only responsive sub-sample in these regressions. Their own-tax and cross-tax elasticities are statistically significant and extremely large, suggesting paid preparers are improving the information set of tax units or are assisting with avoidance activities. The remainder of the sub-populations do not produce any statistically significant point estimates for our variables of interest. In addition, the standard errors are extremely large in most specifications. This suggests collinearity is an issue, which is unsurprising given that sub-samples might exhibit less cross-sectional variation both within and between different tax rate types.

1.6 Capital Gains Tax Elasticities

Now I consider the effect of ordinary income and long-term capital gains tax rates on long-term capital gains realizations. This literature is much smaller, with only three studies estimating capital gains elasticities in the United States in the past twenty years (Burman & Randolph, 1994a; Auerbach & Siegel, 2000; Dowd et al., 2015). Recall that the capital gains estimation equations reflect two aspects of capital gains in the United States that are not issues in the ordinary income setting. First, realizations are taxed, not accruals. Second, the majority of tax units do not have
any realized long-term capital gains in a given year. An individual is assumed to first determine whether to realize capital gains ($I_{it}^*$), then the level of capital gains realizations ($g_{it}$). These two decisions are estimated in a Generalized Tobit framework following Lee et al. (1980).

1.6.1 Long-term Capital Gains Income Estimation Equations

In this section I outline the capital gains approach. The procedure for estimating this system of equations involves four steps, as adapted to this context by Burman and Randolph and most recently implemented by Dowd et al. First, the current ($\tau_{ct}$) and future ($\tau_{ct+1}$) marginal tax rates are replaced with fitted values, generated by regressing those variables on two excluded instruments – first dollar tax rate and highest combined state and federal rate – and the remaining control variables. Second, equation 1.10 is estimated by Probit on the full sample. The dependent variable, $I_{it}^*$, is a binary variable representing whether a net positive long-term capital gains realization took place in year $t$. The estimated coefficients in equation 1.10 are used to construct the Inverse Mills Ratio ($\lambda_{it}$). Third, the fitted values for the current and future marginal tax rates are re-estimated on the sub-sample of observations with positive net realized long-term capital gains, and the Inverse Mills Ratio (IMR) is included as a regressor. Fourth, equation 1.11 is estimated by OLS on the sub-sample, where the dependent variable, $\ln(g_{it})$, is the log-level of net long-term gains from the sale of capital assets. Standard errors are calculated using a standard bootstrapping technique, and a dummy variable for the existence of carryover losses is used as an exclusion restriction between the criteria and level equations.

29 Specifically, the variable used is from line 9 on the Form 1040 Schedule D: net long-term gains or losses from the sale of a capital asset. This variable is prior to applying any carry-over losses or contemporary losses from short-term transactions.
Here are the criteria and level equations, taken (with modification) from Dowd et al.:

\[ I_{it}^* = \alpha_1 \hat{\tau}_{it}^c + \alpha_2 \hat{\tau}_{it-1}^c + \alpha_3 \hat{\tau}_{it+1}^c + X_{it}' \alpha_4 + \gamma_{1it} \]  

(1.10)

\[ \ln(g_{it}) = \beta_1 \hat{\tau}_{it}^c + \beta_2 \hat{\tau}_{it-1}^c + \beta_3 \hat{\tau}_{it+1}^c + X_{it}' \beta_4 + \hat{\lambda}_{it} + \gamma_{2it} \]  

(1.11)

In both equations, the marginal long-term capital gains tax rate for individual \( i \) at time \( t \) is denoted \( \tau_{it}^c \), vectors of control variables are denoted \( X_{it} \), and the error term is denoted \( \gamma_{it} \). Hats denoted fitted values. The control variables include demographic, wealth, and income information. The \( \alpha \) and \( \beta \) parameters are coefficients associated with the regressors.

I modify the standard approach by including the ordinary income tax rates for the previous, current, and next years as right hand side variables in both the level and criteria equations (e.g. \( \tau_{it}^o \)). I instrument for the endogenous ordinary income tax rates (i.e. the current and future year tax rates) in the capital gains estimation equations using predicted tax rates based on previous year’s income.\(^{30}\)

Equation 1.12 and equation 1.13 are my baseline specifications in the capital gains setting:

\[ I_{it}^* = \alpha_1 \hat{\tau}_{it}^c + \alpha_2 \hat{\tau}_{it-1}^c + \alpha_3 \hat{\tau}_{it+1}^c + \alpha_4 \hat{\tau}_{it}^o + \alpha_2 \hat{\tau}_{it-1}^o + \alpha_3 \hat{\tau}_{it+1}^o + X_{it}' \alpha_4 + \gamma_{1it} \]  

(1.12)

\[ \ln(g_{it}) = \beta_1 \hat{\tau}_{it}^c + \beta_2 \hat{\tau}_{it-1}^c + \beta_3 \hat{\tau}_{it+1}^c + \beta_4 \hat{\tau}_{it}^o + \beta_2 \hat{\tau}_{it-1}^o + \beta_3 \hat{\tau}_{it+1}^o + X_{it}' \beta_4 + \hat{\lambda}_{it} + \gamma_{2it} \]  

(1.13)

To be clear, \( \tau_{it}^c \) is the long-term capital gains tax rate for individual \( i \) in tax year \( t \), and \( \tau_{it}^o \) is the analogous ordinary income tax rate. The coefficients with repeated superscripts are “own-tax;” differing superscripts are “cross-tax.” The own-tax “persistent” elasticity is calculated as originally derived by Burman and Randolph (1994b), and

\(^{30}\)This is similar to the approach in the ordinary income setting, except the treatment and instruments are in levels, not differences.
followed by Auerbach and Siegel and Dowd et al.:

\[ \tau_{it+1} \left[ \beta_1^{cc} + \beta_2^{cc} + \beta_3^{cc} + (\alpha_1^{cc} + \alpha_2^{cc} + \alpha_3^{cc}) \lambda_{it} \right] \]

The own-tax “transitory” elasticity is calculated in an analogous manner, dropping the coefficients associated with future and lagged tax rates. Cross-tax elasticities are calculated analogously to their own-tax counterparts, swapping \( \tau_i^c \) for \( \tau_o^c \), and \( \alpha^{cc} \) and \( \beta^{cc} \) for \( \alpha^{co} \) and \( \beta^{co} \). All elasticities are weighted by the product of the size of net long-term gains realized (before deducting any applicable carryover losses from previous years) and the sample weight.

Sample restrictions in this setting are similar to those in the ordinary income setting. The primary difference is that I drop observations with negative long-term capital gains tax rates (of which there are very few), and I expand my analysis to 2000 to 2006. I control for non-tax factors relevant to capital gains realization decisions using a number of variables, including several imputed variables. The log of lagged permanent and transitory income are imputed using regressions of average income in the sample on demographic characteristics. Log unrealized capital gains are imputed from the SCF. The log of lagged business losses and rent losses, along with analogous dummy variables, control for shocks to entrepreneurial income. The number of short term transactions – meant to control for the sophistication of the household – enter in five separate bins, ranging from 1 to 34 transactions (75th percentile) to 1,002 or above (99th percentile). I also include a marriage dummy, number of children, and five year age bins of the primary filer.

Table 1.8 displays means and standard errors for the variables used in this setting for the full sample and the sub-set of tax units reporting positive net long-term capital.

31A negative own-tax elasticity in this setting suggests higher capital gains tax rates lower capital gains realizations. Elasticities in the ordinary income setting have the opposite sign because the \( 1 - \tau \) is used to construct elasticities in the ordinary income setting.
gains realizations ("realizers"). Only 7.5% of the weighted sample are realizers. This compares to roughly 17% of the unweighted sample, which is a consequence of the panel’s over-sampling of high-income individuals. Realizers are also on average older, more likely to be married, and have fewer children.

All of the regression tables in Section 1.6 contain results from the second and fourth steps: the criterion regression (Equation 1.12) and the level regression (Equation 1.13). Columns 1 and 3 are always the criterion equation estimates, and columns 2 and 4 are always the level equation estimates.

1.6.2 CAPITAL GAINS TAX ELASTICITY ESTIMATES

Table 1.9 presents the coefficient estimates, with standard errors (calculated using a standard boot-strapping technique) in parentheses, from the criterion and level equations with and without cross-tax rates. I begin by abstracting away from cross-tax and inter-temporal effects; that is, I assume all ordinary income cross-tax effects are zero as well as the coefficients on lagged and future capital gains tax rates. Columns 1 and 2 are the criterion and level equations when the only tax variable included is the current period capital tax rate. Columns 3 and 4 re-estimate columns 1 and 2 with the addition of the current period ordinary income tax rate.

The tax coefficients match my priors in every case. Current period capital taxes are negatively correlated with capital gains realizations and the amount of realizations. Similarly, higher ordinary income taxes in the current period are associated with a greater probability of realizing a capital gain, and also larger capital gains. All of the elasticity estimates have the correct sign, and are plausible given the broad range of prior transitory estimates. The coefficients associated with the inverse mills ratios in each setting are significantly different from zero, suggesting a “selection” issue is
relevant here. Similarly, the exclusion restriction – the existence of carryover losses in excess of $3,000 – is relevant for realization decisions.

Columns 1 and 2 of Table 1.9 closely follow Dowd et al., and includes the future and lagged tax rates as explanatory variables. This specification involves two endogenous variables, the current and next period tax rates, and both are fitted prior to estimating the criterion and level equations. The coefficient estimates in this setting do not match my priors, with the exception of the lagged tax rate. The transitory elasticity reflects this: it has the wrong sign and is imprecisely estimated. The persistent elasticity, however, is extremely close to that estimated by Dowd et al., -0.899, and is statistically significantly different from zero.

Columns 3 and 4 of Table 1.10 add current, future, and lagged ordinary income tax rates to the mix. The coefficients associated with these variables have the correct sign, except the next period tax rate in the level equation. The resulting persistent cross-tax elasticity estimate is 2.774, with a standard error of 1.233. This is statistically significantly different from zero at a 5 percent level. The transitory elasticity is imprecisely estimated, with a standard error over 5. Including the cross-tax rates flips the signs of the current period capital gains tax rate, and the persistent elasticity is much larger in this case (-2.438). The transitory capital gains elasticity remains insignificant, however.

1.7 Discussion

My paper’s primary contribution is to estimate cross-tax rates between long-term capital gains income and ordinary income in the United States. The tax system in the United States differs in several ways from the only other country in which cross-
tax elasticities have been estimated (Denmark) and there are many reasons to think the elasticities might differ.\textsuperscript{32} I make several other contributions as well.

Most notably, I apply the findings of Caroline Weber’s (2014) work on consistent elasticity of taxable income estimation to a new time period and new set of data. These include constructing instruments for ordinary income that are less likely to be endogenous than instruments constructed following Gruber and Saez (2002), and employing more appropriate base year income controls and income weights.

I find that in the standard framework, ignoring cross-tax effects of capital gains, ordinary income elasticities of taxable income are indistinguishable from zero in the context of the Bush Tax Cuts. These estimates indicate we cannot reject that the tax cuts had non-negligible effects on individual taxable income earning patterns.

When incorporating cross-tax effects I find that estimated ordinary income responses to capital gains taxes are large and statistically significant in some cases and are imprecisely estimated in others. The own-tax estimates – the responsiveness of ordinary income to ordinary income tax changes – similarly vary in size and statistical significance. I explore the responsiveness of various sub-samples that might be more responsive ex ante, and find that those with paid preparers respond to a much larger degree. I also find statistically significant responses by long-term capital gains realizations to ordinary income taxes. Own-tax capital gains responses are also large, which is in keeping with existing work.

Evidence suggesting individuals respond to tax rates across income types by altering income earning or reporting activities has consequences for estimates of revenue and welfare consequences of taxation. To the extent individuals respond across income types, the excess burden and behavioral revenue losses from marginal tax

\textsuperscript{32}Kopczuk (2005) establishes that individuals respond to changes in the definition of income, which makes any cross-country comparisons challenging given that income definitions, avoidance opportunities, and tax enforcement likely vary in myriad ways.
rate increases on a given type of income might not be as large as own-tax elasticities alone would suggest. Similarly, the excess burden reductions and behavioral revenue gains associated with marginal tax decreases could be smaller. This is because income flowing from one income type to another increases in the excess burden or revenue of one income type and decreases with the other. This partially offsets both effects.
Table 1.1: Ordinary Income Panel: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Broad Income</td>
<td>81,333</td>
<td>275,801</td>
</tr>
<tr>
<td>Taxable Income</td>
<td>55,507</td>
<td>231,810</td>
</tr>
<tr>
<td>Ordinary Income MTR</td>
<td>32.0</td>
<td>8.3</td>
</tr>
<tr>
<td>Capital Gains MTR</td>
<td>17.0</td>
<td>7.7</td>
</tr>
<tr>
<td>Married Dummy</td>
<td>58.6</td>
<td>-</td>
</tr>
<tr>
<td>Itemizer Dummy</td>
<td>53.5</td>
<td>-</td>
</tr>
<tr>
<td>Business Income Dummy</td>
<td>23.7</td>
<td>-</td>
</tr>
<tr>
<td>Number of Children</td>
<td>0.8</td>
<td>1.1</td>
</tr>
<tr>
<td>Observations</td>
<td>191,159</td>
<td></td>
</tr>
</tbody>
</table>

Data are limited to base years used in estimation: 2000-2004. Broad and taxable income are denominated in constant year 2005 dollars. Marginal tax rates are inclusive of state income and federal payroll taxes, where applicable. $\Delta$ indicates three-year differences. Sample weights are applied to each item, with the exception of “observations.”
Table 1.2: Ordinary Income Responses: Testing Exogeneity of Instruments

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta \ln (1 - \tau^o) )</td>
<td>0.074</td>
<td>0.074</td>
<td>0.208</td>
<td>0.431</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.077)</td>
<td>(0.269)</td>
<td>(0.451)</td>
</tr>
<tr>
<td>Observations</td>
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<td>101,357</td>
<td>101,357</td>
<td>101,357</td>
</tr>
<tr>
<td>Clusters</td>
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<td>41,616</td>
<td>41,616</td>
<td>41,616</td>
</tr>
<tr>
<td>Number of Lags</td>
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<td>0, 2, 3</td>
<td>1, 2, 3</td>
<td>2, 3</td>
</tr>
<tr>
<td>Diff-in-Sargan</td>
<td>0.41</td>
<td>0.51</td>
<td>0.90</td>
<td></td>
</tr>
<tr>
<td>1st-Stage F Stat</td>
<td>2,263</td>
<td>793</td>
<td>74</td>
<td>63</td>
</tr>
</tbody>
</table>

* \( p < 0.05 \), ** \( p < 0.01 \), *** \( p < 0.001 \)

Estimated coefficients are presented, with tax unit-clustered standard errors in parentheses. These are two-stage least square results, where excluded simulated instruments are constructed using various lags of income. Column 1 uses excluded instruments holding income constant in the base year. Column 2 adds excluded instruments from income lagged two and three periods prior to the base year. Column 3 uses three excluded instruments, constructed using income lagged one, two, and three years. Column 4 uses excluded instruments constructed using income lagged two and three periods. The dependent variable in all four columns is the three-year log change in taxable income. Data are limited to base years 2000-2002. Marginal tax rates are inclusive of federal income, state income, and federal payroll taxes, where applicable. Ten-piece splines in gross income lagged two and three periods prior to the base year are also included as controls. Year and region fixed effects are used, and controls for marital status, age, age-squared, itemizer status, number of children, and the sex of the primary filer are included.
Table 1.3: Ordinary Income Responses: Own-Tax Elasticities

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \ln(1 - \tau^o)$</td>
<td>0.421</td>
<td>0.044</td>
<td>0.498</td>
<td>0.282</td>
<td>0.191</td>
<td>0.330</td>
<td>0.011</td>
<td>0.124</td>
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<tr>
<td></td>
<td>(0.446)</td>
<td>(0.361)</td>
<td>(0.422)</td>
<td>(0.294)</td>
<td>(0.364)</td>
<td>(0.262)</td>
<td>(0.279)</td>
<td>(0.251)</td>
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<td>46,550</td>
<td>42,483</td>
<td>48,982</td>
<td>46,550</td>
<td>44,483</td>
<td>48,982</td>
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<tr>
<td>Year Differences</td>
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<td>2</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>ITT Effect</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Additional Data</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Diff-in-Sargan</td>
<td>0.94</td>
<td>0.35</td>
<td>0.47</td>
<td>0.90</td>
<td>0.36</td>
<td>0.53</td>
<td>0.34</td>
<td>0.35</td>
</tr>
<tr>
<td>1st-Stage F Stat</td>
<td>64</td>
<td>53</td>
<td>70</td>
<td>209</td>
<td>52</td>
<td>254</td>
<td>133</td>
<td>150</td>
</tr>
</tbody>
</table>

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimated coefficients are presented, with tax unit-clustered standard errors in parentheses. These are two-stage least square results, where simulated instruments are constructed using various two and three year lags of income. The dependent variable in all four columns is the log change in taxable income. Columns 1, 3, 4, and 6 use three year differences, the other four columns use two year differences. Data are limited to base years 2000-2002 in columns 3, 5, 6, and 8, and 2000-2004 in the other four columns. The definition of treatment is the actual, realized change in marginal tax rates in columns 1, 2, 3, and 5, and is the predicted change holding income constant at base year levels in the other four columns. Marginal tax rates are inclusive of federal income, state income, and federal payroll taxes, where applicable. Ten-piece splines in gross income lagged two and three periods prior to the base year are also included as controls. Year and region fixed effects are used, and controls for marital status, age, age-squared, itemizer status, number of children, and the sex of the primary filer are included.
Table 1.4: Ordinary Income Responses: Own-Tax and Income Elasticities

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
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<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\Delta \ln(1 - \tau^o))</td>
<td>-0.385</td>
<td>-0.079</td>
<td>0.140</td>
<td>0.001</td>
<td>-0.068</td>
<td>0.290</td>
<td>0.200</td>
<td>0.117</td>
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<tr>
<td></td>
<td>(0.747)</td>
<td>(0.545)</td>
<td>(0.708)</td>
<td>(0.464)</td>
<td>(0.578)</td>
<td>(0.410)</td>
<td>(0.394)</td>
<td>(0.353)</td>
</tr>
<tr>
<td>(\Delta \ln(\text{Virtual Income}))</td>
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<td>-0.021</td>
<td>-0.002</td>
<td>-0.027</td>
<td>-0.025</td>
<td>-0.010</td>
<td>-0.025</td>
<td>-0.034</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.039)</td>
<td>(0.048)</td>
<td>(0.036)</td>
<td>(0.040)</td>
<td>(0.032)</td>
<td>(0.033)</td>
<td>(0.028)</td>
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<tr>
<td>Observations</td>
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<td>114,521</td>
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</tr>
<tr>
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<tr>
<td>ITT Effect</td>
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<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Additional Data</td>
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<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

* \(p < 0.05\), ** \(p < 0.01\), *** \(p < 0.001\)

Estimated coefficients are presented, with tax unit-clustered standard errors in parentheses. These are two-stage least square results, where simulated instruments are constructed using various two and three year lags of income. The dependent variable in all four columns is the log change in taxable income. The definition of treatment is the actual, realized change in marginal tax rates in columns 1, 2, 3, and 5, and is the predicted change holding income constant at base year levels in the other four columns. Marginal tax rates are inclusive of federal income, state income, and federal payroll taxes, where applicable. Ten-piece splines in gross income lagged two and three periods prior to the base year are also included as controls. Year and region fixed effects are used, and controls for marital status, age, age-squared, itemizer status, number of children, and the sex of the primary filer are included.
### Table 1.5: Ordinary Income Responses: Own-Tax and Cross-Tax Elasticities

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \ln(1 - \tau^o)$</td>
<td>1.445**</td>
<td>0.314</td>
<td>1.326**</td>
<td>0.823**</td>
<td>0.364</td>
<td>0.792**</td>
<td>0.196</td>
<td>0.234</td>
</tr>
<tr>
<td></td>
<td>(0.512)</td>
<td>(0.384)</td>
<td>(0.484)</td>
<td>(0.284)</td>
<td>(0.387)</td>
<td>(0.261)</td>
<td>(0.278)</td>
<td>(0.257)</td>
</tr>
<tr>
<td>$\Delta \ln(1 - \tau^c)$</td>
<td>-2.392***</td>
<td>-0.561</td>
<td>-1.202**</td>
<td>-1.561**</td>
<td>-0.314</td>
<td>-0.767*</td>
<td>-0.422</td>
<td>-0.244</td>
</tr>
<tr>
<td></td>
<td>(0.665)</td>
<td>(0.428)</td>
<td>(0.463)</td>
<td>(0.476)</td>
<td>(0.380)</td>
<td>(0.366)</td>
<td>(0.336)</td>
<td>(0.320)</td>
</tr>
</tbody>
</table>

|                | 102,233 | 108,149 | 168,040 | 102,255 | 177,893 | 168,074 | 108,172 | 177,926 |
| Clusters       | 42,439  | 44,425  | 46,511  | 42,443  | 48,932  | 46,514  | 44,432  | 48,937  |
| Year Differences| 3       | 2       | 3       | 3       | 2       | 3       | 2       | 2       |
| ITT Effect     | No      | No      | No      | Yes     | No      | Yes     | Yes     | Yes     |
| Additional Data| No      | No      | Yes     | No      | Yes     | Yes     | No      | Yes     |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimated coefficients are presented, with tax unit-clustered standard errors in parentheses. These are two-stage least square results, where simulated instruments are constructed using various two and three year lags of income. The dependent variable in all four columns is the log change in taxable income. Columns 1, 3, 4, and 6 use three year differences, the other four columns use two year differences. Data are limited to base years 2000-2002 in columns 3, 5, 6, and 8, and 2000-2004 in the other four columns. The definition of treatment is the actual, realized change in marginal tax rates in columns 1, 2, 3, and 5, and is the predicted change holding income constant at base year levels in the other four columns. Marginal tax rates are inclusive of federal income, state income, and federal payroll taxes, where applicable. Ten-piece splines in gross income lagged two and three periods prior to the base year are also included as controls. Year and region fixed effects are used, and controls for marital status, age, age-squared, itemizer status, number of children, and the sex of the primary filer are included.
Table 1.6: Ordinary Income Responses: Own-Tax, Cross-Tax, and Income Elasticities

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \ln(1 - \tau^o)$</td>
<td>0.417</td>
<td>-0.124</td>
<td>0.977</td>
<td>0.565</td>
<td>0.105</td>
<td>0.829*</td>
<td>0.224</td>
<td>0.240</td>
</tr>
<tr>
<td></td>
<td>(0.851)</td>
<td>(0.610)</td>
<td>(0.768)</td>
<td>(0.445)</td>
<td>(0.599)</td>
<td>(0.384)</td>
<td>(0.412)</td>
<td>(0.350)</td>
</tr>
<tr>
<td>$\Delta \ln(1 - \tau^c)$</td>
<td>-2.233**</td>
<td>-0.476</td>
<td>-1.744***</td>
<td>-1.654**</td>
<td>-0.536</td>
<td>-1.173**</td>
<td>-0.437</td>
<td>-0.468</td>
</tr>
<tr>
<td></td>
<td>(0.715)</td>
<td>(0.468)</td>
<td>(0.521)</td>
<td>(0.503)</td>
<td>(0.404)</td>
<td>(0.399)</td>
<td>(0.369)</td>
<td>(0.337)</td>
</tr>
<tr>
<td>$\Delta \ln(\text{Virtual Income})$</td>
<td>-0.052</td>
<td>-0.036</td>
<td>-0.014</td>
<td>-0.032</td>
<td>-0.031</td>
<td>-0.013</td>
<td>-0.031</td>
<td>-0.037</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.037)</td>
<td>(0.042)</td>
<td>(0.035)</td>
<td>(0.037)</td>
<td>(0.031)</td>
<td>(0.032)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Observations</td>
<td>63,860</td>
<td>68,448</td>
<td>110,474</td>
<td>66,106</td>
<td>118,140</td>
<td>114,318</td>
<td>70,223</td>
<td>121,315</td>
</tr>
<tr>
<td>Clusters</td>
<td>31,468</td>
<td>33,445</td>
<td>36,775</td>
<td>31,874</td>
<td>38,902</td>
<td>37,014</td>
<td>33,678</td>
<td>38,971</td>
</tr>
<tr>
<td>Year Differences</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>ITT Effect</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Additional Data</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Estimated coefficients are presented, with tax unit-clustered standard errors in parentheses. These are two-stage least square results, where simulated instruments are constructed using various two and three year lags of income. The dependent variable in all four columns is the log change in taxable income. Columns 1, 3, 4, and 6 use three year differences, the other four columns use two year differences. Data are limited to base years 2000-2002 in columns 3, 5, 6, and 8, and 2000-2004 in the other four columns. The definition of treatment is the actual, realized change in marginal tax rates in columns 1, 2, 3, and 5, and is the predicted change holding income constant at base year levels in the other four columns. Marginal tax rates are inclusive of federal income, state income, and federal payroll taxes, where applicable. Ten-piece splines in gross income lagged two and three periods prior to the base year are also included as controls. Year and region fixed effects are used, and controls for marital status, age, age-squared, itemizer status, number of children, and the sex of the primary filer are included.
Table 1.7: Ordinary Income Responses: Tax Elasticities for Various Sub-Populations

<table>
<thead>
<tr>
<th></th>
<th>$\Delta \ln(1 - \tau^o)$</th>
<th>$\Delta \ln(1 - \tau^e)$</th>
<th>$\Delta \ln($Virtual Income$)$</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Over $50,000$</td>
<td>0.552</td>
<td>-0.168</td>
<td>0.002</td>
<td>82,101</td>
</tr>
<tr>
<td></td>
<td>(0.87)</td>
<td>(0.62)</td>
<td>(0.05)</td>
<td></td>
</tr>
<tr>
<td>Over $100,000$</td>
<td>2.808</td>
<td>-1.104</td>
<td>0.201</td>
<td>42,720</td>
</tr>
<tr>
<td></td>
<td>(1.85)</td>
<td>(0.87)</td>
<td>(0.16)</td>
<td></td>
</tr>
<tr>
<td>Capital Gains Income</td>
<td>0.863</td>
<td>-0.577</td>
<td>0.014</td>
<td>51,608</td>
</tr>
<tr>
<td></td>
<td>(1.09)</td>
<td>(0.79)</td>
<td>(0.08)</td>
<td></td>
</tr>
<tr>
<td>Unearned Income</td>
<td>0.475</td>
<td>-0.419</td>
<td>0.005</td>
<td>93,710</td>
</tr>
<tr>
<td></td>
<td>(0.51)</td>
<td>(0.47)</td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>Pass-through Income</td>
<td>0.956</td>
<td>-0.912</td>
<td>-0.035</td>
<td>45,942</td>
</tr>
<tr>
<td></td>
<td>(1.06)</td>
<td>(0.86)</td>
<td>(0.09)</td>
<td></td>
</tr>
<tr>
<td>Paid Preparer</td>
<td>2.292*</td>
<td>-1.559*</td>
<td>0.079</td>
<td>41,025</td>
</tr>
<tr>
<td></td>
<td>(1.06)</td>
<td>(0.73)</td>
<td>(0.07)</td>
<td></td>
</tr>
</tbody>
</table>

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$  

Estimated coefficients are presented, with tax unit-clustered standard errors in parentheses. These are two-stage least square results, where simulated instruments are constructed using various two and three year lags of income. The dependent variable is the three year log change in taxable income. Base years range from 2000-2004. The definition of treatment is the predicted change holding income constant at base year levels. Marginal tax rates are inclusive of federal income, state income, and federal payroll taxes, where applicable. Ten-piece splines in gross income lagged two and three periods prior to the base year are also included as controls. Year and region fixed effects are used, and controls for marital status, age, age-squared, itemizer status, number of children, and the sex of the primary filer are included.
Table 1.8: Capital Gains Panel: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>Realizers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
</tr>
<tr>
<td>Net Long-term Gains</td>
<td>1,622</td>
<td>195,172</td>
</tr>
<tr>
<td>Percent with Positive Net Gains</td>
<td>7.55</td>
<td>-</td>
</tr>
<tr>
<td>ln(Net Long-term Gains)</td>
<td>0.58</td>
<td>2.14</td>
</tr>
<tr>
<td>ln(Lagged Imputed Permanent Income)</td>
<td>10.69</td>
<td>0.45</td>
</tr>
<tr>
<td>ln(Imputed Transitory Income)</td>
<td>-0.54</td>
<td>1.27</td>
</tr>
<tr>
<td>ln(Imputed Unrealized Gains)</td>
<td>10.63</td>
<td>1.22</td>
</tr>
<tr>
<td>ln(Lagged Business Losses)</td>
<td>0.11</td>
<td>0.97</td>
</tr>
<tr>
<td>ln(Lagged Rental Losses)</td>
<td>0.40</td>
<td>1.80</td>
</tr>
<tr>
<td>Age of Primary</td>
<td>50.6</td>
<td>14.8</td>
</tr>
<tr>
<td>Children</td>
<td>0.77</td>
<td>1.09</td>
</tr>
<tr>
<td>Married Dummy</td>
<td>52</td>
<td>-</td>
</tr>
<tr>
<td>Capital Gains Marginal Tax Rate (MTR)</td>
<td>14.8</td>
<td>8.6</td>
</tr>
<tr>
<td>Ordinary Income MTR</td>
<td>28.4</td>
<td>12.9</td>
</tr>
<tr>
<td>Carryover Loss Dummy</td>
<td>3.54</td>
<td>-</td>
</tr>
<tr>
<td>Observations</td>
<td>291,506</td>
<td>56,108</td>
</tr>
</tbody>
</table>

"Realizers" refers to those who realized net positive long-term capital gains. "Gains" or "Capital Gains" refer to long-term capital gains. Data are limited to base years used in estimation: 2000-2006. Dollar amounts are denominated in constant year 2005 dollars. Marginal tax rates are inclusive of state income and federal payroll taxes, where applicable. Sample weights are applied to each item, with the exception of "observations." Imputed wealth values are from the Survey of Consumer Finance and imputed income variables are from the tax data.
Table 1.9: Transitory Capital Gains Responses to Tax Rates

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \widehat{\tau}_c )</td>
<td>-0.002*</td>
<td>-0.035***</td>
<td>-0.027***</td>
<td>-0.141***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>( \widehat{\tau}_o )</td>
<td>-</td>
<td>-</td>
<td>0.023***</td>
<td>0.091***</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.003)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Inverse Mills Ratio</td>
<td>-</td>
<td>2.420***</td>
<td>-</td>
<td>2.109***</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>(0.306)</td>
<td>-</td>
<td>(0.302)</td>
</tr>
<tr>
<td>ln(Lagged Imputed Permanent Income)</td>
<td>0.198***</td>
<td>1.024***</td>
<td>0.079</td>
<td>0.795***</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.185)</td>
<td>(0.049)</td>
<td>(0.195)</td>
</tr>
<tr>
<td>ln(Imputed Transitory Income)</td>
<td>-0.002</td>
<td>0.071**</td>
<td>-0.038***</td>
<td>-0.008</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.028)</td>
<td>(.007)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>ln(Imputed Unrealized Gains)</td>
<td>0.123***</td>
<td>0.656***</td>
<td>0.011***</td>
<td>0.607***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.039)</td>
<td>(0.007)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Carryover Loss Dummy</td>
<td>0.119***</td>
<td>-</td>
<td>0.126***</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>-</td>
<td>(0.021)</td>
<td>-</td>
</tr>
<tr>
<td>Transitory Elasticity Capital Gains</td>
<td>-0.773***</td>
<td>-3.102***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.087)</td>
<td>(0.629)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transitory Elasticity Ordinary Income</td>
<td>3.614***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.928)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* \( p < 0.05 \), ** \( p < 0.01 \), *** \( p < 0.001 \)

The dependent variable in columns 1 and 3 is the binary decision to realize capital gains or not. The dependent variable in column 2 and 4 is the level of net positive long-term capital gains realizations. Estimated coefficients are presented, with boot-strapped standard errors in parentheses. All tax variables are “fitted”, that is, they are predicted using an OLS regression prior to inclusion in the criterion or level equations. The excluded instrument used for capital gains rates are the first-dollar and maximum rates. The excluded instruments for ordinary income are the predicted rates based on two and three period lagged income. Data are limited to base years used in estimation: 2000-2004. Marginal tax rates are inclusive of state income and federal payroll taxes, where applicable.
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\tau}_{t+1}$</td>
<td>-0.029**</td>
<td>-0.094*</td>
<td>-0.010</td>
<td>-0.131</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.046)</td>
<td>(0.028)</td>
<td>(0.122)</td>
</tr>
<tr>
<td>$\tilde{\tau}_{t}$</td>
<td>0.013</td>
<td>0.014</td>
<td>-0.055</td>
<td>-0.106</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.036)</td>
<td>(0.037)</td>
<td>(0.155)</td>
</tr>
<tr>
<td>$\tilde{\tau}_{t-1}$</td>
<td>0.010***</td>
<td>0.038***</td>
<td>0.035**</td>
<td>0.121**</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.006)</td>
<td>(0.011)</td>
<td>(0.05743)</td>
</tr>
<tr>
<td>Inverse Mills Ratio</td>
<td>-</td>
<td>2.170***</td>
<td>-</td>
<td>2.200***</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>(0.305)</td>
<td>-</td>
<td>(0.334)</td>
</tr>
<tr>
<td>$\tilde{\tau}_{t+1}^o$</td>
<td>-</td>
<td>-</td>
<td>-0.009</td>
<td>0.110</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.027)</td>
<td>(0.116)</td>
</tr>
<tr>
<td>$\tilde{\tau}_{t}^o$</td>
<td>-</td>
<td>-</td>
<td>0.055</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.035)</td>
<td>(0.150)</td>
</tr>
<tr>
<td>$\tilde{\tau}_{t-1}^o$</td>
<td>-</td>
<td>-</td>
<td>-0.022*</td>
<td>-0.078*</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.008)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>ln(Imputed Permanent Income)</td>
<td>0.201***</td>
<td>1.095***</td>
<td>0.077*</td>
<td>0.785***</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.204)</td>
<td>(0.033)</td>
<td>(0.199)</td>
</tr>
<tr>
<td>ln(Imputed Transitory Income)</td>
<td>0.005</td>
<td>0.101**</td>
<td>-0.046***</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.033)</td>
<td>(0.012)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>ln(Imputed Unrealized Capital Gains)</td>
<td>0.127***</td>
<td>0.623***</td>
<td>0.102***</td>
<td>0.626***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.040)</td>
<td>(0.009)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Transitory Elasticity Capital Gains</td>
<td>-</td>
<td>0.316</td>
<td>-</td>
<td>-2.276</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>(0.774)</td>
<td>-</td>
<td>(3.231)</td>
</tr>
<tr>
<td>Persistent Elasticity Capital Gains</td>
<td>-</td>
<td>-0.899***</td>
<td>-</td>
<td>-2.438***</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>(0.169)</td>
<td>-</td>
<td>(0.847)</td>
</tr>
<tr>
<td>Transitory Elasticity Ordinary Income</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>1.677</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>(5.655)</td>
</tr>
<tr>
<td>Persistent Elasticity Ordinary Income</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>2.774*</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>(1.233)</td>
</tr>
</tbody>
</table>

The dependent variable in columns 1 and 3 is the binary capital gains realizations decision. The dependent variable in column 2 and 4 is the level of net positive long-term capital gains realizations. Estimated coefficients are presented with boot-strapped standard errors in parentheses. All tax variables are “fitted.” The excluded instruments used for capital gains rates are the first-dollar and maximum state and federal tax rates. The excluded instruments for ordinary income are the predicted rates based on two and three period lagged income. Data are limited to base years used in estimation: 2000-2004.
Figure 1.1: Effective Marginal Tax Rate Schedules

Figure created using simulated data fed into Bakija’s tax calculator. Household is assumed to be married filing jointly with one dependent living in a state with no income taxes in 2007. The vertical axis is the effective marginal tax rate for a given income type, expressed in percentage points. The horizontal axis is the amount of income of a given type in year 2007 dollars.
Figure 1.2: Differential Between Ordinary Income and Long-Term Capital Gains
Marginal Tax Rates

Figure created using simulated data fed into Bakija’s tax calculator. Household is assumed to be married filing jointly with one dependent living in a state with no income taxes in 2007. The vertical axis is the difference between effective marginal tax rates on ordinary income and long-term capital gains, expressed in percentage points. The horizontal axis is the amount of income of a given type in year 2007 dollars.
Figure 1.3: Effective Marginal Tax Rates: 2000 and 2005

Figure created using simulated data fed into Bakija’s tax calculator. Household is assumed to be married filing jointly with one dependent living in a state with no income taxes in 2007. The vertical axis is the effective marginal tax rate for a given income type, expressed in percentage points. The horizontal axis is the amount of income of a given type in year 2000 dollars.
Figure 1.4: Changes in Effective Marginal Tax Rates: 2000 and 2005

Figure created using simulated data fed into Bakija’s tax calculator. Household is assumed to be married filing jointly with one dependent living in a state with no income taxes in 2007. The vertical axis is the change in effective marginal tax rate for a given income type, expressed in percentage points. The horizontal axis is the amount of income of a given type in year 2000 dollars.
Figure 1.5: Change in the Differential Between Ordinary Income and Capital Gains
Effective MTRs: 2000 to 2005

Figure created using simulated data fed into Bakija’s tax calculator. Household is assumed to be married filing jointly with one dependent living in a state with no income taxes in 2007. The vertical axis is the change in the difference between effective marginal tax rates on ordinary income and long-term capital gains, expressed in percentage points. The horizontal axis is the amount of income of a given type in year 2000 dollars.
Chapter 2

How Sensitive Are Taxpayers to Marginal Tax Rates? Evidence from Income Bunching in the United States

2.1 Introduction

This paper estimates taxpayer responsiveness to changes in marginal income tax rates by measuring the degree to which taxpayers bunch at kinks in the tax schedule. A kink is an income amount for a given taxpayer at which marginal tax rates change discretely, marking the end of one tax bracket and the beginning of the next. Standard economic theory predicts that some taxpayers will avoid brackets with high tax rates by bunching at kinks where tax rates increase, resulting in extra mass in the distribution of income close to these kinks. We measure this excess mass at a wide variety of kinks in the federal tax schedule, building upon methods developed by Saez (2010) and Chetty et al. (2011).

Understanding the way taxpayers respond to the tax code is necessary for welfare and revenue analyses of current and proposed income tax regimes. Possible channels for response include labor supply, labor demand, deduction, and evasion decisions, with each having different implications for welfare (Chetty, 2009). Estimating heterogeneous responses across household types is also important, as the tax code accomplishes different objectives for different groups. For example, low earners receive income subsidies partly designed to increase labor supply, while high earners receive
deductions and credits for activities like charitable giving or improving home energy efficiency.

Economists have long recognized that, absent optimization frictions, kinked budget sets should induce bunching in income distributions. However, the first searches for bunching relied upon survey data and failed to find responses at kinks. Thus, the focus of early work estimating responsiveness to the entire budget set was on fitting models that could identify behavioral responses to marginal tax rates but allowed for a lack of bunching at kinks. Initially this involved parametric assumptions regarding the error term in individuals’ labor supply (Burtless and Hausman, 1978); however, recent work allows for nonparametric identification (Blomquist and Newey, 2002). These non-linear budget set models can be thought of as using responses away from kinks to identify tax rate sensitivity, while using bunching (or the lack thereof) to calibrate optimization frictions.

In contrast, Saez (2010) develops a technique for using bunching to directly estimate responsiveness to marginal tax rates at a given kink. The bunching approach relies on estimating counterfactual income distributions that would hold if there were no kink. Saez uses this method to estimate elasticities of taxable income, analyzing kinks in the Earned Income Tax Credit (EITC) and statutory federal income tax schedules using public-use tax data from 1960 to 2004. He finds substantial bunching only around the first EITC kink and at $0 of taxable income. All other kinks appear to generate no bunching. Importantly, when looking closer at the bunching patterns around the first EITC kink, Saez finds the response is driven entirely by the self-employed. Chetty et al. (2011) offer an alternative approach to constructing counterfactual income distributions. Our technique combines the best aspects of these two approaches, and we show in Appendix A that our bunching measures generally lie between those of Saez and Chetty et al.
In the United States, the bunching approach has also been used to analyze responsiveness to the Annual Earnings Test for Social Security income (Burtless and Moffitt, 1984; Friedberg, 2000; Gelber et al., 2013) and the Saver’s Credit notch (Ramnath, 2013). Elsewhere, bunching has been studied at discontinuities in tax schedules in Denmark (Le Maire and Schjerning, 2013), Sweden (Bastani and Selin, 2014), Pakistan (Kleven and Waseem, 2013), Ireland (Hargarden, 2015), and the United Kingdom (Devereux et al., 2014). Kleven (2016) discusses this research as well as applications of the bunching approach outside of the tax literature.

Our bunching measures use detailed administrative data drawn from the universe of federal income tax returns in the United States from 1996 to 2014. With over 500 million observations in total, most of our estimators – including those for narrowly defined household types in a given year – use tens or hundreds of thousands of observations, resulting in smooth distributions over the intervals surrounding kinks. These data cover approximately 200 times as many taxpayers as the public use files, allowing us to study heterogeneity in responses across household types and across kinks. We study all statutory kinks in the federal tax schedule as well as several effective kinks created by the EITC, Child Tax Credit (CTC), Making Work Pay Tax Credit, American Opportunity Tax Credit, and phase-outs of itemized deductions and personal exemptions.1

We make six contributions to the modern public finance literature estimating income responses to tax rate changes. First, we measure annual variation in responses to taxation over a nineteen-year period that includes two tax reforms and several business cycle fluctuations, including the Great Recession. Second, we derive the

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1We also examine notches related to federal disability insurance and Medicaid, as well as a few high-income kinks in state tax schedules and a kink related to the Supplemental Nutritional Assistance Program. We find no response at any of these discontinuities in marginal incentives. See Section 2.2 and Appendix B for further details.
bunching estimator of Saez (2010) without imposing a functional form on utility. Third, we employ an estimation technique that fits more closely with the theory of discrete kinks and show how our technique compares with those of Saez (2010) and Chetty et al. (2011). Fourth, we provide new evidence of bunching behavior, documenting the emergence of bunching at five kinks where taxpayers were previously unresponsive, including bunching among wage earners. Fifth, we track taxpayers over time, and find individuals locate near kinks in consecutive years at higher rates than individuals in comparable sections of the income distribution. Finally, we show that taxpayers gravitate towards the point of the schedule that maximizes tax credits net of taxes owed, even as this point changes from one kink to another due to small changes in the tax code over time.

Our primary finding is the rapid rise of new bunching patterns at two low-income kinks. Statistically significant and economically meaningful bunching emerges in the mid 2000s at the second EITC kink and the beginning of the refundability plateau of the CTC. The second EITC kink marks the beginning of the credit’s phaseout region and increases effective marginal tax rates by as much as 21 percentage points. The beginning of the CTC refundability plateau marks the point at which the credit becomes fully refundable and increases effective marginal tax rates by 15 percentage points. Like the first EITC kink – another place we see strong bunching, confirming prior research – both of these kinks allow taxpayers to receive the maximum credit amounts, potentially elevating their salience.

We also find weak, but statistically significant bunching at four other kinks for many groups. Consistent with Saez (2010), we see bunching at the beginning of the federal income tax schedule, where tax rates increase by ten percentage points. In addition, we see responsiveness at the second and third kinks in the statutory schedule, where marginal rates increase by ten and three percentage points, respectively. Finally,
we find bunching at the kink that maximizes the Making Work Pay Tax Credit (MWPTC) – a small credit made available to low-income taxpayers in 2009 and 2010 that changes effective marginal tax rates by roughly six percentage points. All other kinks that we study do not generate statistically discernible bunching.

We estimate that in 1996 approximately 165,000 taxpayers bunched at the kinks we study. This is a subset of the total number of taxpayers reporting incomes at these kinks, as some taxpayers would remain there if there were no kink. By 2014, we estimate that roughly 1.1 million taxpayers were bunching. The growth in the bunching phenomenon highlights the changing nature of behavioral responses to taxation, and suggests taxpayers may have more knowledge of the tax code today than in the past. It also suggests that studies of taxpayer behavior based on tax reforms in the 1980s and 1990s may be weak proxies for contemporary responsiveness to marginal tax rates.

In both 1996 and 2014, about 80% of bunchers reported incomes at the first EITC kink, however, the fraction of total bunching that occurs at the first EITC kink is not constant over time. From 2010 to 2011, the first EITC kink saw its share of total bunchers fall from 73% to 60%; from 2012 to 2013, the share rose from 66% to 79%. We hypothesize that these dynamics are due to taxpayers gravitating towards the point in the schedule that maximizes tax credits net of taxes owed. For a given taxpayer, this unique point in the schedule minimizes overall liability, which typically means the taxpayer receives a large refund. For many self-employed taxpayers, this point changed locations in 2011 with the onset of the payroll tax holiday, moving from the first EITC kink to either the second EITC kink or the CTC refundability kink. In 2013, when the holiday had ended, the first EITC kink once again marked the point in the schedule that maximized credits net of taxes owed.
Single, self-employed taxpayers with two children provide clear evidence of this phenomenon. During 2004 to 2008, these taxpayers bunch at the second EITC kink, which maximizes the EITC and earns them a fraction of the CTC, maximizing their overall credits net of taxes owed. During this period, these taxpayers ignore the nearby CTC refundability plateau, which would earn them the full CTC but would reduce their EITC and would increase other taxes owed. During 2009 and 2010, the second EITC kink and the CTC refundability plateau are located at essentially the same place, and the group continues to bunch there. During 2011 to 2014, however, the CTC refundability plateau becomes the point in the schedule that maximizes tax credits net of taxes owed, as the CTC refundability plateau moves below the second EITC kink. By targeting the CTC refundability plateau in those years, taxpayers could earn the maximum EITC and the maximum CTC. Taxpayers could also maximize both credits if they continued to bunch at the second EITC kink, but this would increase their self-employment tax. Taxpayers evidently recognize this, as they shift to bunch at the CTC refundability plateau, ignoring the second EITC kink where they previously bunched.

The key statistic that stands out describing the bunching population is their tendency to report self-employment income. According to the Internal Revenue Service, in 2013 thirteen percent of tax returns reported self-employment income. Among bunchers in our sample in that year, approximately 86% report self-employment income. This also represents the overall figure for the proportion of bunchers reporting self-employment income across all years of our sample. It is unclear whether self-employed bunching responses are distortions of real economic behavior or reporting phenomena. The self-employed are known to exhibit higher rates of noncompliance (Slemrod, 2007), but they also have more flexibility over their work schedule and
may be altering labor hours to bunch. In addition, self-employed taxpayers may make strategic decisions regarding deductible business expenses to locate near kinks.

Wage earners, in contrast, are not allowed any deductions when calculating qualifying income for the EITC and CTC, where most wage earner bunching occurs. Further, wage income is reported by third parties and exhibits substantially less noncompliance than self-employment income (Slemrod, 2007). Thus, the wage earner bunching we see represents prima facie evidence of distortions in real economic behavior. However, the wage earner bunching we observe only occurs in taxpayer reported wages. When we match taxpayers with employer reported W-2s, wage income bunching disappears. We caution that this need not reflect noncompliance, as not all wage and salary income is reported on Form W-2. Taxpayers may have unreported tip income, or small amounts of income below the W-2 filing threshold, that allows them to bunch through legal means. In addition, our data are pre-audit: we only observe what taxpayers report. We cannot say whether the tax credits these taxpayers claim are ever paid out, nor whether they are recovered by the Internal Revenue Service in the event they were paid out but later deemed inaccurate.

2.2 Data and Institutional Background

In this section we briefly describe our data and portions of the U.S. tax code where we find bunching responses. We begin with an overview of our various data sources, followed by discussions of the statutory federal schedule, Earned Income Tax Credit, Child Tax Credit, and Making Work Pay Tax Credit. In Appendix B, we describe the kinks we study that do not generate bunching, which include many statutory kinks, state kinks, and kinks created by phase-outs of personal exemptions, itemized deductions, and other credits.
2.2.1 Data

Our analysis of taxpayer bunching uses data drawn from the Internal Revenue Service’s Compliance Data Warehouse (CDW). The CDW contains the universe of tax returns (e.g., Form 1040 and its schedules) and information returns (e.g., Form W-2) of individuals in the United States. Each observation in our data is a tax unit that filed a tax return for a given year. This could be an individual or a married couple filing jointly. Most of the data consist of fields on the tax return and its schedules. These include ordinary and capital gains income, as well as deductions, credits, and taxes paid. All data are pre-audit and therefore reflect what taxpayers report when filing. Certain demographic information is also found on tax returns, such as marital status, number of children, years of birth of those in the tax unit, and address of residence. We also make use of wage and industry information from the Form W-2 as well as information on date of birth and sex at the time of birth from the Social Security Administration’s Data Master File.

The main set of data is a sample from the CDW consisting of all tax returns in the seven states with no state income taxes: Alaska, Florida, Nevada, South Dakota, Texas, Washington, and Wyoming. We choose this subsample for two reasons. First, the combined population of these states accounts for roughly 20% of the U.S. population and is sufficiently large to identify heterogeneous responses in narrow subpopulations. Second, and most important, state income tax regimes interfere with our analysis by creating new kinks and amplifying existing federal kinks. When state kinks are near the federal kinks we study, they may affect the distribution of income we observe, confounding the identification of responses to federal kinks. When state kinks amplify federal kinks, as in the case of state-level EITCs, ignoring state-specific taxes and subsidies biases upwards potential elasticity estimates.
The second set of data is a ten percent random sample representative of the U.S. filing population with primary filers – those individuals listed first on a tax return – between the ages of 25 and 64 (inclusive). These data contain a randomly generated nine-digit identification number (ID) and we draw the sample based on the last three digits of that number. The panel is unbalanced: tax units whose primary filer has a qualifying ID ending enter the sample by turning age 25. Individuals exit the sample when they are no longer the primary filer listed on a tax return, turn age 65, or die. The panel remains representative of the filing population in any given year as a result of these entrances and exits.

In addition, we draw several other samples for specific kinks. One is a sample from the CDW consisting of all tax returns in the neighborhood of high-income statutory kinks and kinks created by phaseouts of personal exemptions and itemized deductions. Another is a sample of all tax returns that claim the American Opportunity Tax Credit near the beginning of the phase-out of the credit. The mass from the seven states listed above is insufficient to analyze these kinks. Yet another is a sample from the CDW consisting of all tax returns from 2003 to 2014 in California, Connecticut, and New Jersey in the neighborhood of each state’s largest kink.

2.2.2 Federal Tax Code

Despite its well-deserved reputation for complexity, the U.S. federal income tax code has a straightforward statutory schedule.\(^2\) In 1996, the first year in our sample, the schedule for ordinary income had five tax brackets whose marginal tax rates are detailed in Table 2.1.\(^3\) This schedule remained stable on an inflation-adjusted basis.

\(^2\)The complexity comes from the many rules that govern the definition of\(\text{taxable income}\), which is total income less deductions and exemptions, as well as the long list of tax credits available to certain taxpayers.

\(^3\)The actual implementation of Table 2.1’s marginal tax rates involves a large number of \$50 micro-brackets, with discrete changes in tax liability only at the beginning of each
until the Bush Tax Cuts of 2001-2003, which added a 10% bracket at the beginning of the schedule and generally lowered rates.\textsuperscript{4} The Bush tax rates remained in place until the American Taxpayer Relief Act of 2012, which reinstated a top bracket of 39.6%.

The kink points separating the federal tax brackets vary by year and filing status. To keep terminology uniform, throughout the paper we take the “first” kink to be the divider between the first and second brackets according to the post-Bush Tax Cuts schedule. Similarly, we take the “second” kink to be the divider between the second and third brackets, and so on. Thus, in our terminology, the first kink did not exist in 1996-2001 and the sixth kink did not exist in our sample until 2013. The “zeroth” kink marks the beginning of the schedule in all years.

Unlike the EITC and CTC schedules detailed below, the statutory income tax schedule is progressive. All kinks see marginal tax rates increase and are therefore convex. Most of these kinks create small changes in the net-of-tax rate. In the presence of significant optimization frictions, we might not expect bunching at those kinks. Two of the kinks, however, create absolute changes in tax rates of 10 percentage points or more: the zeroth and second statutory kinks. All else equal, we expect to observe stronger responsiveness at these kinks. Estimating bunching at the zeroth kink requires care, however, as it also represents the filing threshold for most tax units. That is, most individuals with taxable income below this kink are not required to file federal income tax returns, potentially creating a censoring problem. We avoid bracket. Hence, the effective tax rate on marginal income is actually zero for most taxpayers for small enough marginal income increments. Like most other researchers, we ignore this, sticking with the simpler approximation of the tax code given by the table. This is valid if taxpayers’ marginal decisions involve dollar increments larger than $50.

\textsuperscript{4}Following convention, we refer to the Economic Growth and Tax Relief Reconciliation Act of 2001 and the subsequent Jobs and Growth Tax Relief Reconciliation Act of 2003 collectively as the “Bush Tax Cuts.”
this issue by only examining self-employed taxpayers, as their filing threshold is $400 of self-employment income during our sample period. We further limit this sample to those taxpayers with no dependents to abstract away from refundable tax credits related to children.

2.2.3 Earned Income Tax Credit

The EITC is one of the largest poverty alleviation policies (and tax expenditures) in the United States, with some 28.8 million low-income tax units receiving $68 billion dollars in 2013. These figures have grown since 1996, when roughly 19.5 million tax units received $28.8 billion. All low-income taxpayers between the ages of 25 and 64 are eligible, and the age restriction only applies to taxpayers with no qualifying children. The credit’s schedule varies based on filing status (single or married), number of qualifying children, and tax year. Childless households may qualify for a small credit (a maximum of $496 in 2014), but the EITC is substantially more generous for households with children. For example, a taxpayer with three qualifying children in 2014 could potentially receive a credit of $6,143.

The term “earned” in the credit’s title refers to the definition of income to which the credit applies: labor and self-employment income. As earned income increases from zero, all households face a phase-in region, a plateau, and a phase-out region. In the phase-in region, additional earned income is subsidized at rates between 7.65% and 45% depending on the number of qualifying dependents in the household. In the plateau region, the taxpayer receives the maximum credit amount. Each additional dollar of qualifying income does not affect the credit amount. In the phase-out region,

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5 See Eissa and Hoynes (2011) and Nichols and Rothstein (2015) for detailed discussions of the EITC.

6 These figures are taken from the Statistic of Income’s “Tax Stats” website, specifically the section on the EITC here: http://www.irs.gov/Individuals/Earned-Income-Tax-Credit-Statistics.
the subsidy is removed at rates between 7.65% and 21.06%, again depending on the number of qualifying dependents. The phase-out increases effective tax rates in this region, potentially discouraging reported earned income.\footnote{Phaseout of the EITC occurs using the greater of earned income and adjusted gross income (AGI). In our empirical analysis we ignore this issue, assuming all taxpayers have weakly greater earned income than AGI. Our measures, therefore, likely understate responsiveness at the second EITC kink.}

We expect individuals to bunch around the first and second kinks, marking the beginning and end of the plateau region. Because it is non-convex, the kink at the end of the phase-out region should induce an absence of mass. Previous studies have not identified responses at non-convex kinks, but for many taxpayers this kink creates the largest percentage change in the net-of-tax rate. Thus, if we see a response to any non-convex kinks, we expect it here.

2.2.4 Child Tax Credit

The Child Tax Credit (CTC) is available to taxpayers on a per child basis, but phases out for those above certain income thresholds. As with the EITC, the CTC phases in as a function of earned income.\footnote{Technically it is the Additional Child Tax Credit – the refundable portion of the CTC – that phases in. See Crandall-Hollick (2013) for a detailed description of the credit and its legislative history.} The credit amount and refundability parameters have varied since the credit’s introduction in 1997. Initially the CTC was $400 per qualifying child. In 1999 it increased to $500; in 2001 and 2002 the credit was $600; and in 2003 the credit increased to its present value of $1,000 per qualifying child.

The credit creates two convex and two non-convex kinks. The first non-convex kink is the refundability threshold, which was introduced in 2001. At this threshold the portion of the credit exceeding the taxpayer’s liability can be claimed by the individual, but only at a rate of 10% or 15% of earned income exceeding the threshold,
depending on the year. This has no effect on households whose tax liability exceeds the credit amount. For the remaining households, however, the kink effectively decreases marginal tax rates by 10% or 15%. The threshold was $10,000 from 2001 to 2007 (indexed to inflation beginning in 2002), reduced in 2008 to $8,500, and reduced again in 2009 to $3,000 (no longer indexed to inflation). The refundability rate was 10% from 2001 to 2003 and 15% after.

The first convex kink occurs at the point where the CTC has been fully refunded. After this point the credit is fully maximized, creating a plateau region. The kink at the beginning of the refundability plateau is comparable to the first EITC kink, where the credit is maximized and creates a plateau. As other research has found bunching at the first EITC kink, the beginning of the CTC refundability plateau is perhaps the most likely place to find a bunching response to the CTC.

The second convex kink is at the end of the credit’s plateau and the beginning of the phase-out region, which is $75,000 for singles and $110,000 for married filing jointly (neither are indexed to inflation). The credit is reduced by $50 for every $1,000 in additional modified adjusted gross income (MAGI), effectively increasing marginal tax rates by five percentage points. The end of the phase-out region – where the credit amount is completely eliminated – marks the second non-convex kink. At this point the taxpayer’s marginal tax rate decreases ceteris paribus. In a frictionless world, we would expect an absence of mass at this point. However, given that marginal tax rates change by only five percentage points, we do not expect to find responsiveness at either the beginning or end of the CTC phaseout region.

2.2.5 Making Work Pay Tax Credit

The Making Work Pay Tax Credit was a refundable tax credit available to low-income and middle-income workers in 2009 and 2010. The credit was administered through a
reduction in withholdings on Form W-2, and as a result many low-income individuals received the credit even without filing a tax return. The credit effectively reduced the tax rate on earned income by 6.2% up to $6,451 of earned income for singles and $12,903 of earned income for married couples filing jointly. The maximum credit amounts were $400 and $800 for singles and married couples, respectively. The credit began to phase-out at a rate of roughly 2% at $150,000 of MAGI for married couples filing jointly and $75,000 for all others, and was fully exhausted at $190,000 and $95,000, respectively.

The end of the phase-in region, beginning of the phase-out region, and end of the phase-out region all created kinks. However, we only expect responsiveness at the first kink, for two reasons. First, it is a relatively large, convex kink: 6.2 percentage points for all returns. Second, it maximizes a refundable tax credit and was a salient component of the American Recovery and Reinvestment Act of 2009. The other kinks are relatively small, and the incentives they create are easily overwhelmed by moderate optimization frictions.

2.3 Bunching Analysis

We now turn to documenting bunching patterns at the kinks described in the previous sections. Figure 2.1 shows the location of the kinks we study for a single filer with two children in 2014. The horizontal axis is taxable income (comprised entirely of wage income), and the vertical axis is the marginal tax rate (ignoring state taxes). Kinks with increasing marginal tax rates are convex, while those with decreasing marginal tax rates are non-convex. The size of each kink is given in Table 2.2, where size is

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9 The sizes and locations of the kinks are different for taxpayers with different filing status, household size, or self-employment status. Also, many kinks do not exist for tax units without dependents.
measured by the percentage change of the marginal net-of-tax rate (one minus the marginal tax rate).\textsuperscript{10} The five largest kinks occur at gross incomes below $50,000, reflecting the strong distortions of the EITC and CTC. There are, however, some sizable kinks at high incomes as well. The sixth largest kink is the second statutory kink, occurring at $71,250, where statutory rates rise from 15% to 25%. In addition, there are moderately-sized kinks at $75,000 and $113,700, at the beginning of the CTC phase-out and the threshold for FICA taxes, respectively.

In general, if taxpayers are sensitive to marginal tax rates and optimization frictions are small, all convex kinks will generate bunching (Saez, 2010). However, at most kinks there is no evidence of responsiveness in any of the years of our sample. This includes the largest kink in Figure 2.1, the non-convex kink at the end of the EITC phase-out region (the seventh kink in the schedule). Standard theory predicts a dip in the distribution of income near a non-convex kink. We do not observe this in the data, even for groups that are highly sensitive to other kinks.

We also see no response at most statutory kinks, including all high-income kinks. In addition to exploring federal high-income kinks, we analyze the largest high-income kinks created by state tax regimes, which occur in California, Connecticut, and New Jersey. These state kinks are small (less than three percentage point changes), but occur at income levels greatly exceeding any federal kink (up to $2 million). We find no evidence of bunching at any of these kinks during any of the years in our sample period. All of the bunching patterns we observe occur at incomes below $75,000, and the strongest patterns occur at kinks below $25,000.\textsuperscript{11}

\textsuperscript{10}We measure kink size in this way because the percentage change in the marginal net-of-tax rate corresponds to the denominator in the conventional definition of the elasticity of taxable income.

\textsuperscript{11}In addition, in Appendix B we test for bunching at income eligibility thresholds for various transfer programs, including Medicaid, SNAP, and disability benefits. We find none,
Our broad finding of zero responsiveness implies that taxable income is insensitive to marginal tax rates in the neighborhood of most kinks. This could be driven by several mutually compatible causes. First, gathering information about the tax schedule is costly and taxpayers may have imperfect knowledge of their local tax schedule, consistent with Chetty and Saez (2013). Second, taxpayers may not base their decisions on marginal incentives, as in Ito (2014). Third, taxpayers may know their local schedule and want to respond to marginal incentives, but may be constrained by optimization frictions such as adjustment costs or lumpy earnings opportunities. This explanation is consistent with Gelber et al. (2013), but is less convincing when deduction opportunities are present (e.g. at statutory kinks). Deductions, such as charitable giving, allow taxpayers to precisely manipulate their taxable income at the end of the year, after gross income is observed. Fourth, marginal tax rates are functions of annual income and deductions. Individuals respond to marginal tax rates throughout the year based on expectations of income and deduction activity. If income is sufficiently volatile or expectations are sufficiently imprecise, taxpayers may fail to respond to kink points. This problem is potentially compounded by the presence of multiple income earners and income types.

When kinks are small, the hypothesis that taxpayers ignore marginal incentives is particularly appealing. Chetty (2012) shows that ignoring many of the kinks in the tax schedule leads to utility losses of less than 1% compared to a utility-maximizing choice. In light of this, the lack of responsiveness at most middle-income and all high-income kinks is unsurprising.

Taxpayers are not universally unresponsive, however. We observe bunching at several low- and middle-income kinks. Similar to patterns documented in Saez (2010) though annual tax return data – as opposed to data with finer temporal variation – are not well suited to analyze these programs, whose eligibility criteria are primarily monthly.
and Chetty et al. (2013), we find sharp bunching at the first EITC kink in all years of our sample. This is where the strongest bunching occurs. We also document bunching at the zeroth statutory federal kink, consistent with Saez (2010). In addition, we provide new evidence of bunching at the second EITC kink, CTC refundability plateau kink, MWPTC kink, and the second and third statutory kinks. Responsiveness at the two EITC kinks, the CTC kink, and the second statutory kink are displayed in Figure 2.2 for selected years and household types. We explore these patterns in detail in the following sections.

2.3.1 Estimation Technique

When measuring bunching, the key issue is how taxpayers would behave in the absence of a kink. In particular, we must specify an alternative local tax schedule as well as the local distribution of income under the alternative tax schedule. We estimate this counterfactual behavior separately for two scenarios, corresponding to the two marginal tax rates (MTRs) that hold above and below the kink. We refer to the MTR that applies below the kink as $t_0$, and the MTR that applies above it as $t_1$. First, for those bunchers located below (left of) the kink, we estimate their behavior under a locally constant MTR equal to $t_0$. In other words, we assume their MTR continues unchanged throughout the kink region. Second, for those bunchers located above (right of) the kink, we estimate their behavior under a locally constant MTR equal to $t_1$, assuming their MTR also held below the kink.

In estimating these counterfactual scenarios separately, we break from the bunching analysis developed by Chetty et al. (2011). To our knowledge, all extant research that reports bunching coefficients uses their style of estimating one counterfactual distribution for bunchers on both sides of the kink. Though not always made explicit, the underlying assumption for their counterfactual tax schedule is a
constant MTR equal to \( t_0 \), as their estimation equation is derived by taking the limit as \( t_1 \) converges to \( t_0 \). We estimate the two scenarios separately to better link with the theory of discrete kinks.\(^{12}\) We compare our methods with those of Chetty et al. (2011) and Saez (2010) in Appendix A. In general, our methods produce bunching coefficients (and elasticities) smaller than Saez’s and larger than those of Chetty et al.

For each counterfactual scenario, we estimate the income distribution using observed data near the kink but not so close as to be affected by bunching behavior. Specifically, we group households into bins and estimate distinct linear projections on both sides of the kink. For the counterfactual scenario where the MTR is \( t_0 \), we use bins \(-R, ..., -1, 0\), where bin 0 contains the kink. For the counterfactual scenario where the MTR is \( t_1 \), we use bins \( 0, 1, ..., R \). We call the union of these sets of bins the “bunching region.”

For the counterfactual scenario where the MTR is \( t_0 \), we estimate the following equation by ordinary least squares:

\[
y_j = \alpha^0 + \beta^0 z_j + \sum_{k=-W}^{0} \gamma_k^0 \cdot 1[j = k] + \varepsilon_j^0, \quad (2.1)
\]

where \( y_j \) denotes the number of taxpayers in bin \( j \), \( z_j \) denotes the income level of bin \( j \), \( W \) denotes the number of bins in the bunching window near the kink, and \( \varepsilon_j^0 \) denotes the residual.\(^{13}\) Parameters \( \gamma_k^0 \) capture the number of taxpayers in the bunching

\(^{12}\)An additional concern with the approach of Chetty et al. is that it uses the existing income distribution above the kink (i.e. under MTR \( t_1 \)) to inform the counterfactual distribution under MTR \( t_0 \). Saez (2010) shows these distributions are generally not equal, nor are they directly proportional. Thus it is unclear what, if any, information the actual distribution above the kink offers when estimating the counterfactual distribution under MTR \( t_0 \).

\(^{13}\)We tried including higher-order polynomial terms of \( z_j \), but this would often over-fit the data, producing unrealistic counterfactual projections inside the bunching window.
window unexplained by the linear prediction \((\alpha^0 + \beta^0 z_k)\). In other words, \(\gamma_k^0\) measures the amount of excess mass in bin \(k\) relative to the counterfactual expectation.

For the counterfactual scenario where the MTR is \(t_1\), we estimate a similar equation:

\[
y_j = \alpha^1 + \beta^1 z_j + \sum_{k=0}^{W} \gamma_k^1 \cdot 1[j = k] + \varepsilon_j^1.
\]

(2.2)

Our default parameter values, which we select by visual inspection, are a bin-width of \(\$100\) (\(\delta = \$100\)), a bunching region of 71 bins (\(R = 35\)), and a bunching window of 21 bins (\(W = 10\)).\(^{14}\) Our default counterfactuals are therefore derived from the actual distribution of income between \(\$1,000\) and \(\$3,500\) away from each kink. Letting circumflexes denote estimated coefficients, we calculate the total number of bunchers as

\[
\hat{B} = \sum_{k=-W}^{-1} \hat{\gamma}_k^0 + \sum_{k=1}^{W} \hat{\gamma}_k^1 + (1/2)(\hat{\gamma}_0^0 + \hat{\gamma}_0^1).
\]

Figure 2.3 graphically depicts this estimation technique for married filers near the second statutory kink in 2002. The estimated number of bunchers is simply the difference between the observed and counterfactual distributions of income inside the bunching window.

In a few instances, two kinks are too close together to perform the analysis as described. Suppose we wish to analyze kink \(K\), but kink \(L\) lies somewhere inside \(K\)’s bunching region. If taxpayers bunch at \(L\), this can lead to unreasonable estimates for the counterfactual distributions needed for \(K\)’s analysis. For this reason we do not report bunching coefficients for kink \(K\) whenever (i) taxpayers bunch at some kink \(L\), and (ii) the distance between kinks \(K\) and \(L\) is between \(\$1,000\) and \(\$2,000\). When the distance between the kinks is less than \(\$1,000\), so that kink \(L\) lies within kink \(K\)’s bunching window, the problem is not the estimates for \(K\)’s counterfactual distributions. Instead, the difficulty is that it is hard to tell which kink bunchers are

\(^{14}\)We show that our results are robust to parameter choice in Appendix A.
responding to. In this case, we estimate the total number of bunchers in the usual way, except we divide them into two groups. If kink \( K \) sees marginal tax rates change by \( \Delta t_K \), and kink \( L \) sees marginal tax rates change by \( \Delta t_L \), then we assign fraction \( \Delta t_K / (\Delta t_K + \Delta t_L) \) to \( K \), and one minus this fraction to \( L \).

Regardless of whether other kinks are nearby, the total number of bunchers is a flawed metric for taxpayer responsiveness. All else equal, the number of bunchers will be larger when analyzing kinks affecting a larger mass of taxpayers. Hence, we report a unitless bunching coefficient \( \hat{b} \) equal to \( \hat{B} \) (or the fraction thereof assigned to the kink being analyzed) divided by the average number of non-bunchers in $100 bins inside the bunching window. In other words, letting \( P_k \) denote the observed population in bin \( k \), we define

\[
\hat{b} \equiv \frac{\hat{B}}{\left[ \sum_{k=-W}^{W} P_k - \hat{B} \cdot \frac{\$100}{\delta} \right] / (2W + 1)}.
\]

We use a bootstrap procedure to obtain standard errors for \( \hat{B} \) and \( \hat{b} \) by adding randomly sampled estimated residuals (from the original regressions) to the predicted values of the original regressions, repeatedly estimating \( \hat{B} \) and \( \hat{b} \) from the new, simulated data.\(^{15}\)

2.3.2 Bunching Estimation Results

Though all taxpayers face incentives to bunch at the convex kinks of Figure 2.2, some taxpayers are more responsive to these incentives than others. To compare bunching patterns across groups, Table 2.3 presents estimated bunching coefficients at four kinks where we find a response, using our most recent five years of data. In general,

\(^{15}\)We thank Raj Chetty, John Friedman, Tore Olsen, and Luigi Pistaferri for public provision of a Stata program designed specifically to implement their estimation technique. Our code builds directly on theirs, and we plan to make our code publicly available in the near future.
the first EITC kink elicits the largest response. It sees the largest bunching coefficient, 21.85, corresponding to single, self-employed individuals. The bunching coefficient indicates the mass of bunchers is approximately 22 times the average number of non-bunchers in $100 bins inside the bunching window. This implies 51% of single, self-employed taxpayers in the bunching window (i.e. within $1,000 of the kink) are there because of the changing marginal incentives at the kink.\(^{16}\) According to the theory developed by Saez (2010), these taxpayers desire income greater than the kink when facing the low tax rate, and income less than the kink when facing the high tax rate.\(^{17}\)

Contrasting with prior research, we observe wage earners (i.e. those without self-employment income) bunching at many kinks in recent years. Single wage earners, in particular, exhibit statistically significant bunching coefficients at the first EITC kink, second EITC kink, CTC refundability plateau, and second statutory kink beginning in the early to mid-2000s. Married-filing-separately wage earners bunch at the third statutory kink, but married-filing-jointly wage earners do not exhibit statistically significant bunching at any kink in any year. However, as shown in Table 2.3, the magnitude of responses by wage earners is much smaller than those with self-employment income. All of the statistically significant bunching coefficients for the self-employed are larger than those of their wage-earning counterparts in 2010-2014, and most of these differences are themselves statistically significant.

\(^{16}\)To see this, let \(X\) denote the average number of non-bunchers in $100 bins inside the bunching window. Then \(\hat{B} = \hat{b} \cdot X\), and the fraction of bunchers among the population within $1,000 of the kink is \(\hat{b} \cdot X / (21X + \hat{b} \cdot X) = \hat{b} / (21 + \hat{b}) \approx 0.51\) for \(\hat{b} = 21.85\).

\(^{17}\)Other groups and other kinks exhibit smaller, statistically insignificant bunching coefficients that are occasionally negative. Negative numbers imply the kink causes less mass to locate near the kink. This is plausible only if the ETI is negative, which has little empirical support. As none of the negative coefficients are statistically distinguishable from zero, we interpret them as evidence that taxpayers are not responding to the kink.
It is unclear, though, whether the greater responsiveness of the self-employed can be attributed to greater real labor responses or higher rates of tax evasion. One the one hand, manipulating earned income is inherently easier when one is both the employer and employee, so the self-employed likely exhibit larger real labor responses. Moreover, self-employment income is easily adjusted at the end of the tax year by incurring business expenses. On the other hand, unlike wage income, self-employment income is not subject to third-party reporting and is therefore easier to hide from tax authorities (or inflate when income is subsidized). Thus, the self-employed likely exhibit larger tax evasion responses as well.

Because wage earnings are reported by third parties, they are thought to be more reliable indicators of real economic activity (Slemrod, 2007). Further, because EITC kinks are determined by gross income, adjustments or itemized deductions are irrelevant. Thus, at first glance, our results seem to indicate wage-earner bunching is generated by real labor supply (or demand) responses. However, in Section 2.4.1 we show that bunching in taxpayer-reported wages does not manifest in employer-reported wages.

In addition to the four kinks of Table 2.3, we document weak, but statistically significant bunching at the zeroth and third kinks in the statutory schedule.\textsuperscript{18} The former coincides with the filing threshold for wage earners, and therefore suffers from censoring in the data. In addition, taxpayers with children do not see a change in marginal incentives at this kink because the non-refundable portion of the Child Tax

\textsuperscript{18}We primarily observe bunching through earned income, as opposed to adjusted gross income or taxable income. The amount of information needed to calculate adjusted gross income (total income net of adjustments) and taxable income (adjusted gross income net of deductions) is larger than that needed to calculate earned income. For this reason, annual taxable income forecasts necessary to bunch at statutory kinks are strictly noisier than analogous earned income forecasts necessary to bunch at EITC kinks or the CTC refundability plateau.
Credit immediately eliminates their liability. Thus, we can cleanly measure bunching here only for childless, self-employed taxpayers. The bunching coefficients we observe are more stable over time for married taxpayers than singles, but both groups produce small (0.2 to 0.9), statistically significant bunching in roughly half of the years in the sample.

At the third statutory kink we face no inherent sample restrictions, yet we find statistically significant bunching only for married taxpayers who file separately from their spouse. Other groups, including married couples filing jointly, fail to respond during any years of our sample. At this kink and all kinks above it, we analyze the universe of tax returns because the mass in the seven states comprising our main sample is insufficient to distinguish bunching from noise. Among married taxpayers who file separately, we find stronger responsiveness among wage earners than the self-employed. The former bunch in most years of our sample and see bunching coefficients up to 1.33 (with a standard error of 0.22), while the latter bunch in only a handful of years.

Finally, we see responsiveness to the temporary Making Work Pay Tax Credit by married, self-employed taxpayers with two or more children. In 2009 and 2010, this credit created a convex kink of roughly six percentage points at the end of its phase-in. When fully phased in, the credit delivered $800 to married taxpayers filing jointly. Unfortunately, given its proximity to the first EITC kink for the responsive households, our bunching and elasticity estimates require assumptions about which bunchers near the kink are assigned to the EITC and MWPTC kinks. Nonetheless, Figure 2.4 clearly shows separate responses to each kink, indicating some taxpayers were responding specifically to the MWPTC.
Evolution of Bunching Patterns

One of the most striking features of the bunching patterns we observe is their evolution over time. In 1996, substantial bunching occurs only at the first EITC kink and only for those with self-employment income. Bunching coefficients in that year do not exceed six. By 2014, there is substantial bunching at several kinks, including wage-earner bunching, and bunching coefficients at the first EITC kink reach as high as 33.9 (corresponding to single, self-employed taxpayers with one child).

Figure 2.5 displays this temporal variation. Several findings emerge from studying the figure. First, bunching coefficients are generally increasing over time. Second, in the aggregate, substantial wage-earner bunching (with coefficients exceeding unity) is nonexistent until emerging in 2010 at the first EITC kink. This is why we find wage-earner bunching where Saez (2010) and Chetty et al. (2013) found none, as their samples end in 2004 and 2009, respectively. Third, bunching by the self-employed in response to the CTC emerges in 2009, and the CTC’s coefficients for singles rise rapidly to levels previously achieved only at the first EITC kink. This is especially noteworthy given that the CTC kink changes effective marginal tax rates by 15 percentage points, whereas the first EITC kink sees effective marginal tax rates rise by up to 45 percentage points.

Though responsiveness is generally increasing, in a few instances bunching coefficients fall quite dramatically. For example, the second EITC kink sees a drop in bunching following a peak in 2011. The CTC refundability plateau also sees bunching coefficients fall in recent years. In addition, the first EITC kink sees less bunching by all groups in 2008 at the onset of the Great Recession. An intriguing hypothesis is that economic downturns may influence taxpayers’ ability to bunch, which has been shown to occur in Ireland (Hargarden, 2015). Figure 2.6, which gives our estimates
for the total number of bunchers at the kinks we study, is consistent with this hypothesis. In the aggregate, bunching rises in virtually every year of our sample, but it falls dramatically in 2008.

2.4 EXPLANATIONS FOR BUNCHING VARIATION

We have documented substantial bunching at many large kinks and some small kinks in the effective marginal tax rate schedule. These responses indicate taxpayers have sophisticated knowledge of the tax code as well as the ability and willingness to precisely control their reported incomes. However, we have said little about what form responsiveness takes. There are four general avenues of response to labor income taxation: labor supply, labor demand, deductions, and tax evasion. In this section, we investigate these channels. In addition, we show that bunching responses are significantly more likely to occur at the point in the schedule that maximizes tax credits net of taxes owed.

2.4.1 WAGE-EARNER BUNCHING: TAX EVASION OR REAL RESPONSE?

It is difficult to disentangle the various mechanisms available for bunching when taxpayers are self-employed. As these taxpayers are both employer and employee, labor supply and demand responses are conflated. And because the tax schedule is defined with respect to net self-employment income, it is challenging to distinguish income responses from deduction responses. If a taxpayer reports $15,000 in income and $5,000 in expenses in order to bunch at a $10,000 kink, we cannot know whether she first chose income and then adjusted expenses to land near the kink, or vice versa.
Further, because net self-employment income is not subject to third-party reporting, it is difficult to detect non-compliance responses without thorough audits.\footnote{Audit data can help to identify evasion responses. In a tax audit experiment in Denmark, Kleven et al. (2011) find that around half of the bunching response of the self-employed is eliminated post-audit. We intend to explore this in the U.S. context in future research.}

We have more traction, however, with analysis of pure wage earners. For this group, the taxable-income definition at the kinks where we observe large responses (created by the EITC and CTC) does not allow for deductions, immediately ruling out this channel. In addition, all employers that pay an employee more than more than $600 in a given year are required to file form W-2 with the IRS.\footnote{If any taxes are withheld, even employees earning less than $600 must have a W-2 filed. Household employees have a looser threshold: $1,900 in 2014.} Because of this third-party reporting, wage income is thought to be subject to significantly less non-compliance than self-employment income (Slemrod, 2007). Moreover, we can test for systematic mismatches between taxpayer-reported and employer-reported wage income.

Figure 2.7 displays the distributions of taxpayer- and employer-reported wage income for those taxpayers for which we observe W-2 wages. We highlight taxpayers with two children in 2014, although the patterns are broadly similar for singles with varying number of kids in other recent years. Looking first at the distributions for singles in panel (a), we see that above roughly $25,000 in income, the two distributions are virtually identical. This is consistent with prior research suggesting taxpayer-reported wages are highly reliable. However, below $25,000 a different picture emerges. There is a significant amount of extra mass in the distribution of taxpayer-reported wages in the EITC plateau region (between the two solid vertical bars). This extra mass exhibits sharp bunching precisely at the CTC refundability plateau (marked by the dashed bar); however, employer-reported wages show no indication of bunching at

\[80\]
any kink. This rules out the possibility of a labor demand response to kinks, leaving labor supply and non-compliance as the possible channels.

The evidence is different for the married taxpayers of panel (b). There is no excess mass in the EITC plateau region, and no bunching in either taxpayer-reported or employer-reported wages. We do see more mass in taxpayer-reported wages at incomes above $25,000, but this is unlikely to be driven by taxpayer reporting behavior. Marginal tax rates are positive in this region, so taxpayers have no strategic reason to fabricate income in this region. A more plausible explanation is that we are unable to perfectly match primary filers’ Forms 1040 with secondary filers’ Forms W-2. In other words, for a number of dual-earner households we may be observing only one spouse’s W-2 wage income.

We caution, however, that a mismatch between taxpayer- and employer-reported earnings does not necessarily reflect non-compliance. Relative to the distribution of employer-reported income, the distribution of taxpayer-reported income has more mass in the EITC plateau region and less mass below $10,000. Thus, bunching among wage earners is driven primarily by taxpayers reporting more than their employer-reported wages. This is consistent with reporting requirements if taxpayers report tip income their employers failed to document on their W-2, or additional earnings below the W-2 filing threshold (generally $600, but $1,900 for household employees) from other employers. Thus, we cannot rule out a labor supply response that is concentrated among these income types. However, we also cannot rule out non-compliance in the form of fabricated earnings, under-reported additional income, or self-employment income mis-characterized as wage income.\footnote{Reporting self-employment income as wage income allows taxpayers to avoid paying Social Security and Medicare taxes that mirror payroll taxes on wage income.}
2.4.2 Bunching to Maximize Credits Net of Taxes Owed

In Section 2.3.2, we demonstrated that bunching patterns are not constant over time. The bunching response at a given kink changes at both the extensive and intensive margins. For example, bunching at the CTC refundability plateau and the second EITC kink is nonexistent until emerging in the 2000s. Similarly, in many instances bunching coefficients rise at one kink at the same time another kink sees coefficients fall. We hypothesize this is due to taxpayers seeking the point in the schedule that maximizes tax credits net of taxes owed.

Fortunately, we can test this hypothesis, as different groups see different kinks mark the point in the schedule that maximizes tax credits net of taxes owed. Moreover, within the same groups this point sometimes changes from one year to another due to relatively small changes in the tax code. To see this, consider Figure 2.8, which displays income distributions for single, self-employed taxpayers with two children from 2010 to 2013. In all panels, the point in the schedule that maximizes tax credits net of taxes owed is marked by a solid vertical line. In 2010 this point is the first EITC kink for single, self-employed taxpayers with two children.

However, in 2011 the point that maximized tax credits net of taxes owed shifted to the point where CTC refundability is maximized. This happened for two reasons. First, the amount of income necessary for the CTC to be fully refundable is not indexed to inflation, while the EITC income amounts are indexed to inflation. In 2011, the CTC kink was located just before the second EITC kink, whereas in previous years it was located just after. Second, a temporary two percentage point reduction in employee payroll taxes was enacted in 2011 as part of the Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act of 2010.
Revealing their sophistication, taxpayers immediately respond. A large mass shifts from the first EITC kink to the beginning of the CTC refundability plateau. Bunching coefficients at the first EITC kink fall from 15.8 to 9.6, while at the CTC kink they rise from 2.1 to 4.8, and at the nearby second EITC kink they rise from 4.5 to 7.1\textsuperscript{22}. The distribution of income looks similar in 2012, as the CTC kink remains the point in the schedule that maximizes tax credits net of taxes owed. However, in 2013, the payroll tax holiday ends and the first EITC kink reclaims its status as the point in the schedule that maximizes tax credits net of taxes owed. Once again, taxpayers immediately respond by shifting to the new optimum; bunching plummets at the CTC kink while it soars at the first EITC kink.

We see this behavior among married couples as well. Figure 2.9 displays income distributions for the married counterparts to Figure 2.8. They also see the point in the schedule that maximizes tax credits net of taxes owed shift from the first EITC kink to the CTC refundability plateau in 2011 and then back to the first EITC kink in 2013. Similar to their single counterparts, they respond immediately to each of these shifts.

We also observe sophisticated behavior tracking the point in the schedule that maximizes tax credits net of taxes owed among single wage earners (recall that married wage earners do not bunch). Figure 2.10 shows these patterns for single wage earners with two children. In 2008, the second EITC kink is the point in the schedule that maximizes tax credits net of taxes owed for this group, and that is where the only significant bunching occurs. Then, from 2009 to 2011 the second EITC kink is in essentially the same location as the CTC refundability plateau, and taxpayers continue to bunch there. However, in 2012 the two kinks separate, as the second kink

\textsuperscript{22}Recall that when two kinks are this close, we assign the total mass to each kink in proportion to the size of the kink. See Section 2.3.1 for further detail.
EITC kink increases due to inflation indexing, leaving behind the CTC kink as the new, unique point in the schedule that maximizes tax credits net of taxes owed. In 2013 and 2014 (not pictured), the kinks continue to separate, and in all three years bunching clusters sharply around with CTC kink, with taxpayers essentially ignoring the second EITC kink.

2.4.3 Learning to Bunch? Examining Bunching Persistence

In the previous section, we demonstrate that a portion of taxpayers respond in sophisticated ways to changes in the effective tax schedule over time. However, we know little about the composition of this group of taxpayers. In this section we explore the persistence of bunching by individuals at three kinks where we observe bunching: the first EITC kink, second EITC kink, and CTC refundability kink. We also separately examine the point in the tax code that maximizes credits net of taxes owed.

This analysis relies on tracking individuals over time. We use a ten percent random sample of tax returns with primary filers between the ages of 25 and 64 (inclusive). This panel, described in Section 2.2, is representative of the national filing population in a given year, but is unbalanced: individuals can enter or exit the panel for a variety of reasons. We limit our data to tax units with dependents, resulting in a sample of roughly 80 million observations from 1996 to 2014 (approximately 10 million tax units). The average age of a primary filer in our sample is 41, the average earned income is $75,340 in 2014 dollars, and 60 percent are married.

We measure persistence in proximity to kinks, examining taxpayers who report income within $500 (in 2014 dollars) of a given kink and who maintain the same filing status in consecutive years. The parameter of interest is the likelihood that these taxpayers will remain near the kink in the subsequent year. Of course, a certain percentage of individuals will remain in a given income range for reasons independent
of behavioral responses to taxation. To get a sense of what percentage of measured persistence is driven by secular income dynamics, we estimate the probability that individuals persist in placebo bins that do not contain kinks.

We present two estimates of persistence probabilities in Table 2.4. The first probability estimate is the proportion of taxpayers that locate near a given kink in year \( t + 1 \) conditional on three characteristics: the taxpayer was located near the kink in year \( t \), the taxpayer has the same filing status in years \( t \) and \( t + 1 \), and the taxpayer is in our sample in both years (i.e. the taxpayer filed a tax return, had at least one dependent, and the was between ages 25 and 64). The second probability estimate is a simple extension of the first: what is the probability a taxpayer locates near a kink in year \( t + 2 \), conditional on locating near a given kink in \( t \) and \( t + 1 \), maintaining a constant filing status in all three years, and remaining in the sample in all three years.

The persistence patterns of Table 2.4 exhibit three weakly consistent orderings. Singles persist more than married filers, the probability of persisting twice is higher than the probability of persisting once (often twice as large), and the magnitude of persistence probabilities decrease in the following order: the first EITC kink, the kink associated with the point that maximizes credits net tax owed (often the first EITC kink), the CTC refundability kink, and the second EITC kink. The comparison groups suggest the baseline rate of persistence is higher for singles than married filers. Low-income singles persist once at a rate of 11 percent, and persist twice at a rate of 8 percent. Low-income married filers persist at rates of only 3 percent and 2 percent, respectively.

Single filers near the first EITC kink exhibit the highest levels of persistence: 23 percent of those who locate near a given kink in \( t \) are located near the same kink in \( t + 1 \), and 39 percent of those individuals are located near the same kink in \( t + 2 \).
These are substantially larger than the rates in the comparison group. Importantly, the probability of persisting twice is much higher than the probability of persisting once, whereas the probability of persisting twice in the comparison group is lower than the probability of persisting once. This phenomena is consistent across all filing types and kinks, though in some cases the probability of persisting once is similar in the group near the kink and the comparison group.

Our results are also strongly suggestive of individuals purposefully persisting near kinks over time, especially at the first EITC kink. As with other responses, it is unclear whether this behavior is a reporting phenomenon or the result of real economic responses to these kinks. Intertemporal responses could have consequences for welfare analyses of these credits to the extent such responses are real and distort patterns of income progression over the life cycle.

2.5 DISCUSSION

We have estimated the responsiveness of income to changes in marginal tax rates by measuring the degree to which taxpayers bunch at kink points in income tax schedules in the United States. Our exploration of federal and state statutory kinks, deduction and exemption phase-outs, Earned Income Tax Credit kinks, American Opportunity Tax Credit kinks, and Child Tax Credit kinks indicates most kinks do not generate statistically discernible bunching responses. In particular, all non-convex kinks fail to induce an observable response, nor do we see any responsiveness among high-income taxpayers at the federal or state income tax kinks we study.

However, we discover economically meaningful bunching at several large, convex kinks in the tax schedule, with statistically significant bunching occurring at a total of seven kinks. Consistent with Saez (2010) and Chetty et al. (2013), the first EITC kink
elicits the strongest response. Bunching there occurs during all years of our sample, 1996 to 2014, and increases in intensity over the course of the sample.

We also find evidence of new bunching responses, most notably at the beginning of the CTC refundability plateau and the second EITC kink. Bunching there does not occur at the beginning of our sample but emerges during the mid 2000s. In addition, we find small but visually compelling, statistically significant responses at the largest statutory kink, the beginning of the statutory schedule, the third statutory kink, and the temporary Making Work Pay Tax Credit kink.

At the beginning of our sample, only self-employed taxpayers bunch at kinks. By the end, wage earners bunch at several kinks. However, these patterns are limited to taxpayer-reported wage income. When examining employer-reported wage income, bunching patterns vanish. It is not clear whether this is the result of taxpayers reporting tips their employers failed to document or whether taxpayers are non-compliant.

There are several interesting intertemporal aspects of bunching. First, bunching is a multi-year phenomenon: taxpayers respond to kinks repeatedly, persisting at kinks more than otherwise-similar taxpayers persist at non-kink points of the income distribution. Second, bunching intensity is increasing over time. Third, the total number of bunchers has increased by an order of magnitude in recent decades.

Finally, we present a new explanation of why bunching occurs at some kinks and not others. A substantial fraction of taxpayers appear to target the point in the tax schedule that maximizes tax credits net of taxes owed. Large shifts in mass of bunchers over time across kinks are consistent with this behavior. To the extent this is the case, these individuals are not behaving according to the standard model which posits that larger kinks should induce greater bunching. Exploring the theoretical implications of such targeted behavior remains an interesting avenue for future research.
Table 2.1: Federal Ordinary Income Taxes: Statutory Marginal Tax Rates (%)

<table>
<thead>
<tr>
<th>Bracket</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
<th>4th</th>
<th>5th</th>
<th>6th</th>
<th>7th</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996-2000</td>
<td>—</td>
<td>15</td>
<td>28</td>
<td>31</td>
<td>36</td>
<td>39.6</td>
<td>—</td>
</tr>
<tr>
<td>2001</td>
<td>—</td>
<td>15</td>
<td>27.5</td>
<td>30.5</td>
<td>35.5</td>
<td>39.1</td>
<td>—</td>
</tr>
<tr>
<td>2002</td>
<td>10</td>
<td>15</td>
<td>27</td>
<td>30</td>
<td>35</td>
<td>38.6</td>
<td>—</td>
</tr>
<tr>
<td>2003-2012</td>
<td>10</td>
<td>15</td>
<td>25</td>
<td>28</td>
<td>33</td>
<td>35</td>
<td>—</td>
</tr>
<tr>
<td>2013-2014</td>
<td>10</td>
<td>15</td>
<td>25</td>
<td>28</td>
<td>33</td>
<td>35</td>
<td>39.6</td>
</tr>
</tbody>
</table>

The location of the kinks are adjusted for inflation annually. Taxpayers must update their knowledge of tax schedules annually in order to bunch. See Figure 2.1 for a graphical depiction of the schedule, including effective kinks created by income phase-outs associated with credits.

Figure 2.1: Kinks Faced by a Single Parent with Two Children in 2014

The vertical axis is marginal tax rates, the horizontal axis is taxable income. We assume that the taxpayer (i) only has wage income, (ii) pays no state income taxes, (iii) has $10,000 in itemized deductions, and (iv) claims the EITC and CTC. We ignore the Alternative Minimum Tax. To measure PEP kink sizes we take the most conservative approach, assuming the marginal increment to income is $2,500. See Appendix C for further discussion of this assumption. FICA refers to the Federal Insurance Contributions Act tax, which applies to earned income up to a year-specific cap. Kinks associated with the Making Work Pay Tax Credit – applicable in 2009 and 2010 – are not pictured here.
Table 2.2: Kinks Faced by a Single Parent with Two Children in 2014, Ranked by Size

<table>
<thead>
<tr>
<th>Kink</th>
<th>Gross Income</th>
<th>Percentage Point ΔNTR</th>
<th>Percent ΔNTR</th>
<th>Response for some group during our sample?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Third EITC kink</td>
<td>$47,756</td>
<td>+21.06</td>
<td>+37.41</td>
<td>No</td>
</tr>
<tr>
<td>First EITC kink</td>
<td>$13,650</td>
<td>−40.00</td>
<td>−27.15</td>
<td>Yes</td>
</tr>
<tr>
<td>Second EITC kink</td>
<td>$17,830</td>
<td>−21.06</td>
<td>−22.80</td>
<td>Yes</td>
</tr>
<tr>
<td>Zeroth statutory kink</td>
<td>$21,850</td>
<td>−10.00</td>
<td>−14.03</td>
<td>Yes</td>
</tr>
<tr>
<td>CTC refundability plateau</td>
<td>$16,333</td>
<td>−15.00</td>
<td>−13.97</td>
<td>Yes</td>
</tr>
<tr>
<td>Second statutory kink</td>
<td>$71,250</td>
<td>−10.00</td>
<td>−12.93</td>
<td>Yes</td>
</tr>
<tr>
<td>Beginning of CTC refundability</td>
<td>$3,000</td>
<td>+15.00</td>
<td>+11.33</td>
<td>No</td>
</tr>
<tr>
<td>Threshold for FICA taxes</td>
<td>$113,700</td>
<td>+06.20</td>
<td>+09.94</td>
<td>No</td>
</tr>
<tr>
<td>First statutory kink</td>
<td>$34,800</td>
<td>−05.00</td>
<td>−08.16</td>
<td>No</td>
</tr>
<tr>
<td>Beginning of CTC phase-out</td>
<td>$75,000</td>
<td>−05.00</td>
<td>−07.42</td>
<td>No</td>
</tr>
<tr>
<td>Sixth statutory kink</td>
<td>$454,050</td>
<td>−04.60</td>
<td>−07.34</td>
<td>No</td>
</tr>
<tr>
<td>End of CTC phase-out</td>
<td>$114,000</td>
<td>+05.00</td>
<td>+07.29</td>
<td>No</td>
</tr>
<tr>
<td>Fourth statutory kink</td>
<td>$228,450</td>
<td>−05.00</td>
<td>−07.18</td>
<td>No</td>
</tr>
<tr>
<td>Beginning of PEP and Pease</td>
<td>$257,800</td>
<td>−03.52</td>
<td>−05.45</td>
<td>No</td>
</tr>
<tr>
<td>End of PEP</td>
<td>$380,300</td>
<td>+02.53</td>
<td>+04.08</td>
<td>No</td>
</tr>
<tr>
<td>Third statutory kink</td>
<td>$149,400</td>
<td>−03.00</td>
<td>−04.08</td>
<td>No</td>
</tr>
<tr>
<td>Fifth statutory kink</td>
<td>$426,950</td>
<td>−02.00</td>
<td>−03.09</td>
<td>No</td>
</tr>
<tr>
<td>End of Pease</td>
<td>$287,800</td>
<td>+00.99</td>
<td>+01.62</td>
<td>No</td>
</tr>
<tr>
<td>Additional Medicare Tax threshold</td>
<td>$200,000</td>
<td>−00.90</td>
<td>−01.28</td>
<td>No</td>
</tr>
</tbody>
</table>

Kinks are ranked in descending size, measured by percent change in the net-of-tax rate. See the caption of Figure 2.1 for our assumptions.
Table 2.3: Average Bunching Coefficients Calculated at Four Kinks (2010-2014)

<table>
<thead>
<tr>
<th>Household Type</th>
<th>1st EITC kink</th>
<th>2nd EITC kink</th>
<th>CTC refundability plateau</th>
<th>2nd statutory kink</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single, wage earners</td>
<td>2.13</td>
<td>0.49</td>
<td>—</td>
<td>(0.26)</td>
</tr>
<tr>
<td></td>
<td>(0.29)</td>
<td>(0.28)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[N=2,649,000]</td>
<td>[N=3,138,000]</td>
<td></td>
<td>[N=2,569,000]</td>
</tr>
<tr>
<td>Single, self-employed</td>
<td>21.85</td>
<td>1.27</td>
<td>—</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>(1.09)</td>
<td>(1.14)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[N=2,279,000]</td>
<td>[N=1,517,000]</td>
<td></td>
<td>[N=373,000]</td>
</tr>
<tr>
<td>Married filing jointly, wage earners</td>
<td>0.73</td>
<td>-0.25</td>
<td>0.36</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td>(0.91)</td>
<td>(0.61)</td>
<td>(0.50)</td>
<td>(0.12)</td>
</tr>
<tr>
<td></td>
<td>[N=309,000]</td>
<td>[N=545,000]</td>
<td>[N=670,000]</td>
<td>[N=1,154,000]</td>
</tr>
<tr>
<td>Married filing jointly, self-employed</td>
<td>9.08</td>
<td>1.26</td>
<td>5.25</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>(0.98)</td>
<td>(0.68)</td>
<td>(1.47)</td>
<td>(0.35)</td>
</tr>
<tr>
<td></td>
<td>[N=425,000]</td>
<td>[N=307,000]</td>
<td>[N=555,000]</td>
<td>[N=126,000]</td>
</tr>
<tr>
<td>Married filing separately, wage earners</td>
<td>—</td>
<td>—</td>
<td>0.42</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(1.73)</td>
<td>(0.38)</td>
</tr>
<tr>
<td></td>
<td>[N=24,000]</td>
<td>[N=134,000]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married filing separately, self-employed</td>
<td>—</td>
<td>—</td>
<td>4.10</td>
<td>-0.92</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(3.18)</td>
<td>(1.27)</td>
</tr>
<tr>
<td></td>
<td>[N=4,000]</td>
<td>[N=170,000]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Weighted-average bunching coefficients are reported for various household types, with standard errors in parentheses. The number of taxpayers in the bunching region (rounded to the nearest thousand) is presented in brackets. Wage earners are those with positive wage income and zero self-employment income. The self-employed are those with positive self-employment income. Single status includes “head of household” filers. Estimates are omitted when the kink is between $1,000 and $2,000 away from another kink where taxpayers bunch, as discussed in Section 2.3.1. Married filers who file separately are ineligible for the EITC and thus are excluded from its analysis. The income definition is earned income for the EITC and CTC kinks, and taxable income for the statutory kinks.
Table 2.4: Persistence Within $500 of Kinks

Probability of locating near kink, conditional on...

<table>
<thead>
<tr>
<th>Probability</th>
<th>Single</th>
<th>Married</th>
<th>Single</th>
<th>Married</th>
</tr>
</thead>
<tbody>
<tr>
<td>being near kink last year</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credits Net of Taxes</td>
<td>0.22</td>
<td>0.14</td>
<td>0.37</td>
<td>0.27</td>
</tr>
<tr>
<td></td>
<td>[N=826,939]</td>
<td>[N=230,163]</td>
<td>[N=131,390]</td>
<td>[N=25,285]</td>
</tr>
<tr>
<td>1st EITC kink</td>
<td>0.23</td>
<td>0.15</td>
<td>0.39</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>[N=779,220]</td>
<td>[N=201,473]</td>
<td>[N=128,732]</td>
<td>[N=24,726]</td>
</tr>
<tr>
<td>2nd EITC kink</td>
<td>0.12</td>
<td>0.08</td>
<td>0.22</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>[N=579,983]</td>
<td>[N=213,934]</td>
<td>[N=57,381]</td>
<td>[N=14,064]</td>
</tr>
<tr>
<td>CTC refundability plateau</td>
<td>0.16</td>
<td>0.08</td>
<td>0.32</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>[N=486,193]</td>
<td>[N=187,122]</td>
<td>[N=49,448]</td>
<td>[N=11,378]</td>
</tr>
<tr>
<td>Placebo kinks</td>
<td>0.11</td>
<td>0.03</td>
<td>0.08</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>[N=12,888,916]</td>
<td>[N=7,482,419]</td>
<td>[N=5,419,089]</td>
<td>[N=2,539,533]</td>
</tr>
</tbody>
</table>

Figures calculated from an unbalanced panel of tax returns, representative of the U.S. tax filing population with dependents. Probabilities are calculated conditional on remaining in our panel data and retaining the same filing status over two years (three years for the probabilities conditional on being near a kink two years). The control group persistence rates are calculated by estimating the probability that a taxpayer remains in placebo bins in two or three consecutive years, with the same conditions as the other groups. Placebo bins are $1,000 wide and run from $5,000 to $35,000, however we exclude any bins containing one of the kinks listed in the table. All dollar amounts discussed here are 2014 dollars.
Table 2.5: Robustness Check 1: Bunching Coefficients Calculated at the First EITC Kink in 2003

<table>
<thead>
<tr>
<th></th>
<th>Bunching coefficient</th>
<th>Sample size</th>
<th>Bin-width</th>
<th>Bunching window</th>
<th>Bunching region</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single, self-employed, one child</td>
<td>32.48 (1.11)</td>
<td>116,000</td>
<td>$100</td>
<td>$1,000</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>22.62 (0.87)</td>
<td>116,000</td>
<td>$100</td>
<td>$500</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>37.30 (1.97)</td>
<td>116,000</td>
<td>$100</td>
<td>$1,500</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>31.80 (1.36)</td>
<td>109,900</td>
<td>$100</td>
<td>$1,000</td>
<td>$3,000</td>
</tr>
<tr>
<td></td>
<td>34.26 (1.14)</td>
<td>121,500</td>
<td>$100</td>
<td>$1,000</td>
<td>$4,000</td>
</tr>
<tr>
<td></td>
<td>32.48 (1.20)</td>
<td>115,700</td>
<td>$50</td>
<td>$1,000</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>33.82 (1.23)</td>
<td>116,900</td>
<td>$250</td>
<td>$1,000</td>
<td>$3,500</td>
</tr>
<tr>
<td>Single, self-employed, two children</td>
<td>23.18 (1.19)</td>
<td>106,500</td>
<td>$100</td>
<td>$1,000</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>13.20 (0.85)</td>
<td>106,500</td>
<td>$100</td>
<td>$500</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>32.55 (1.77)</td>
<td>106,500</td>
<td>$100</td>
<td>$1,500</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>20.47 (1.26)</td>
<td>100,900</td>
<td>$100</td>
<td>$1,000</td>
<td>$3,000</td>
</tr>
<tr>
<td></td>
<td>25.16 (1.29)</td>
<td>111,100</td>
<td>$100</td>
<td>$1,000</td>
<td>$4,000</td>
</tr>
<tr>
<td></td>
<td>23.18 (1.17)</td>
<td>106,200</td>
<td>$50</td>
<td>$1,000</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>26.06 (1.36)</td>
<td>107,200</td>
<td>$250</td>
<td>$1,000</td>
<td>$3,500</td>
</tr>
</tbody>
</table>

Bunching coefficients are reported for married, self-employed filers with one or two children. Standard errors are in parentheses. The table shows the sensitivity of our estimates to variation in the estimation parameters, reported in the final three columns. Sample size reports the number of taxpayers within the bunching region and is rounded to the nearest hundred. The self-employed are those with positive self-employment income. Single status includes “head of household” filers. Taxpayers under 25 or over 65 years of age who do not have children are ineligible for the EITC and are therefore excluded.
Table 2.6: Robustness Check 2: Bunching Coefficients Calculated at the First EITC Kink in 2003

<table>
<thead>
<tr>
<th>Married filing jointly, self-employed, one child</th>
<th>Bunching coefficient</th>
<th>Sample size</th>
<th>Bin-width</th>
<th>Bunching window</th>
<th>Bunching region</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>15.40 (0.94)</td>
<td>34,700</td>
<td>$100</td>
<td>$1,000</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>12.66 (0.50)</td>
<td>34,700</td>
<td>$100</td>
<td>$500</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>13.08 (1.41)</td>
<td>34,700</td>
<td>$100</td>
<td>$1,500</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>15.57 (1.17)</td>
<td>31,800</td>
<td>$100</td>
<td>$1,000</td>
<td>$3,000</td>
</tr>
<tr>
<td></td>
<td>16.73 (0.96)</td>
<td>37,600</td>
<td>$100</td>
<td>$1,000</td>
<td>$4,000</td>
</tr>
<tr>
<td></td>
<td>15.40 (0.83)</td>
<td>34,500</td>
<td>$50</td>
<td>$1,000</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>15.37 (0.94)</td>
<td>35,100</td>
<td>$250</td>
<td>$1,000</td>
<td>$3,500</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Married filing jointly, self-employed, two children</th>
<th>Bunching coefficient</th>
<th>Sample size</th>
<th>Bin-width</th>
<th>Bunching window</th>
<th>Bunching region</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>13.72 (1.15)</td>
<td>44,100</td>
<td>$100</td>
<td>$1,000</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>8.47 (0.67)</td>
<td>44,100</td>
<td>$100</td>
<td>$500</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>19.71 (1.84)</td>
<td>44,100</td>
<td>$100</td>
<td>$1,500</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>11.28 (0.99)</td>
<td>40,000</td>
<td>$100</td>
<td>$1,000</td>
<td>$3,000</td>
</tr>
<tr>
<td></td>
<td>14.66 (1.06)</td>
<td>47,800</td>
<td>$100</td>
<td>$1,000</td>
<td>$4,000</td>
</tr>
<tr>
<td></td>
<td>13.72 (0.97)</td>
<td>43,900</td>
<td>$50</td>
<td>$1,000</td>
<td>$3,500</td>
</tr>
<tr>
<td></td>
<td>15.56 (1.07)</td>
<td>44,600</td>
<td>$250</td>
<td>$1,000</td>
<td>$3,500</td>
</tr>
</tbody>
</table>

Bunching coefficients are reported for married, self-employed filers with one or two children. Standard errors are in parentheses. The table shows the sensitivity of our estimates to variation in the estimation parameters, reported in the final three columns. Sample size reports the number of taxpayers within the bunching region and is rounded to the nearest hundred. The self-employed are those with positive self-employment income. Taxpayers under 25 or over 65 years of age who do not have children are ineligible for the EITC and are therefore excluded.
Panels (a) and (b) feature all EITC-eligible filers in our main sample, from 1996 to 2014 and 2002 to 2014, respectively, with the following exception. When the kinks are within $2,000, we drop all taxpayer types in (a) that respond to the second kink, and we drop all taxpayer types in (b) that respond to the first kink. Panel (c) includes all taxpayers, except those that have investment income, in all years of our sample. Panel (d) includes all taxpayers in our sample that have children, except those located within $2,000 of the first or second EITC kinks, from 2004 to 2014. Panels (a), (b), and (d) use $100 binwidths, while panel (c) uses $200 binwidth.
The distribution of income is displayed for married couples filing jointly in 2002 who have no investment income. The estimation parameters are $R = 18$, $W = 5$, and $\delta = \$200$. Fitted lines $h_0$ and $h_1$ denote our estimates for the counterfactual densities of income under the assumptions that the constant marginal tax rate is equal to $t_0$ (the rate below the kink) and $t_1$ (the rate above the kink), respectively.
Income distributions are displayed for married, self-employed taxpayers with two or more children. The dashed vertical line denotes the first EITC kink; the solid line denotes the MWPTC kink. The self-employed are those with positive self-employment income. Married taxpayers who file separately from their spouse are excluded. The figures look very similar using 2009 data.
Figure 2.5: Bunching Over Time at Three Kinks

Trends in bunching coefficients at three kinks are displayed. Wage earners are those with positive wage income and zero self-employment income. The self-employed are those with positive self-employment income. Single status includes “head of household” filers. For the Child Tax Credit coefficients, childless taxpayers are excluded.
Estimates for the total number of bunchers at four kinks are displayed.

Distributions of taxpayer-reported and employer-reported wages from $600 to $50,000 are displayed for those taxpayers for which we observe a Form W-2. The solid vertical bars mark the first and second EITC kinks, and the dashed vertical bar denotes the CTC refundability plateau. Wage earners are those with positive wage income and zero self-employment income. Single status includes “head of household” filers. Taxpayer-reported wages are derived from Form 1040, whereas employer-reported wages are derived from Form W-2.
Figure 2.8: Tracking the Kink that Maximizes Credits Net of Taxes Owed: Singles

(a) Single, self-employed, two children (2010)

(b) Single, self-employed, two children (2011)

(c) Single, self-employed, two children (2012)

(d) Single, self-employed, two children (2013)

Income distributions are displayed for single, self-employed taxpayers with two children from 2010 to 2013. The solid vertical line denotes the kink that maximizes credits net of taxes owed, while dashed vertical lines denote other kinks where taxpayers respond. Single status includes “head-of-household” filers. Returns are deemed to have self employment income if they file Schedule SE with their Form 1040.
Figure 2.9: Tracking the Kink that Maximizes Credits Net of Taxes Owed: Married Couples

(a) Married, self-employed, two children (2010)

(b) Married, self-employed, two children (2011)

(c) Married, self-employed, two children (2012)

(d) Married, self-employed, two children (2013)

Income distributions are displayed for married-filing-jointly tax units with self employment income and two children from 2010 to 2013. The solid vertical line denotes the kink that maximizes credits net of taxes owed, while dashed vertical lines denote other kinks where taxpayers respond. Married couples who file separately are excluded. Returns are deemed to have self employment income if they file Schedule SE with their Form 1040.
Figure 2.10: Tracking the Kink that Maximizes Credits Net of Taxes Owed: Single Wage Earners

(a) Single, wage-earners, two children (2008)  
(b) Single, wage-earners, two children (2009)  
(c) Single, wage-earners, two children (2010)  
(d) Single, wage-earners, two children (2011)  
(e) Single, wage-earners, two children (2012)  
(f) Single, wage-earners, two children (2013)

Income distributions are displayed for single taxpayers with two children from 2008 to 2013. The solid vertical line denotes the kink that maximizes credits net of taxes owed, while dashed vertical lines denote other kinks where taxpayers respond. Single status includes “head-of-household” filers. Wage earners are those with zero self-employment income.
The distribution of income is displayed for various household types in 2003. Single status includes “head of household” filers. The self-employed are those with positive self-employment income.
Chapter 3

The Effect of Required Minimum Distribution Rules on Withdrawals from Traditional Individual Retirement Accounts

3.1 Introduction

Individual Retirement Accounts (IRAs) are an important source of retirement savings for a large portion of the population. We estimate that over six trillion dollars in wealth was held in IRAs by approximately 45 million Americans in 2013.\(^1\) The plans were created to encourage working-age individuals to save for their retirement, as they allow individuals to delay the taxation of both their contributions and the investment income accruing within the plans. Under current law, individuals may not keep their full balances in the tax-deferred account indefinitely. A certain fraction of the IRA balance must be withdrawn each year beginning the year the account-holder turns 70.5 years of age, with the required fraction increasing in age.\(^2\) In this paper, we examine the effect of these required minimum distribution (RMD) rules on distributions (i.e. withdrawals) from traditional IRAs. We find that the rules represent a binding constraint for a large fraction of individuals, and that they also play a role in determining unconstrained distribution behavior. Understanding these responses is crucial for revenue and welfare analyses of retirement savings policy.

\(^1\)This estimate was performed using perfected cross-sections of Form 5498, produced by the Statistics of Income division of the Internal Revenue Service.

\(^2\)A distribution is required corresponding to the year the account-holder turns 70.5 years of age, but this may be delayed until the following year. Approximately 85% of individuals take their first required distribution – the distribution associated with the year they turn 70.5 – in the year that they turn 70.5, with only 15% delaying to the following year.
The tax expenditures used to encourage saving through traditional IRAs are substantial, estimated to be $11.1 billion in 2013 (Joint Committee on Taxation, 2013). RMD rules help to limit these tax expenditures by mandating distributions, which are taxed as ordinary income. Some policymakers are actively considering proposals to change RMDs. In a policy change that we exploit for identification of the effect of the RMD rules on behavior, the rules were temporarily suspended in 2009. Specifically, on December 23, 2008, in a provision of the Worker, Retiree, and Employer Recovery Act of 2008, Congress suspended the RMD rules for one year, likely in response to decreasing account balances associated with the Great Recession. Except for the 2009 suspension, the RMD schedule has remained relatively stable over the last 20 years, with a small change in 2002 to adjust for increasing life expectancies.

A large literature studies the effect of retirement savings policies on contributions to retirement savings accounts (Gale and Scholz, 1994; Engen et al., 1996; Poterba et al., 1996; Madrian and Shea, 2001; Bernheim, 2002; Chetty et al., 2014). In addition, there is a growing literature that studies the withdrawal patterns of retirement savings assets (Sabelhaus, 2000; Bershadker and Smith, 2006; French et al., 2006; Love and Smith, 2007; Coile and Milligan, 2009; Poterba et al., 2011, 2013, 2015; Holden and Bass, 2014; Bryant and Gober, 2013; Argento et al., 2015). However, relatively few studies rigorously analyze the effect of decumulation policies, such as the RMD rules, on withdrawals from retirement accounts. To better understand optimal retirement savings policy, research is needed on the effects of policy on savings and consumption during both working-age and retirement-age years. In this paper, we seek to inform the

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3For example, in January 2016 Representative Sensenbrenner of the U.S. House of Representatives introduced a bill, H.R. 4357, to suspend the RMD rules in 2016.

4In 2002, the entire RMD schedule was relaxed due to a change in the life expectancy tables used by the IRS. We plan to incorporate this policy change into our analysis.
latter.\(^5\) In one of few papers to study the effects of RMD rules on distributions from tax-deferred retirement savings accounts, Brown et al. (2014) use proprietary data on roughly 64,000 accounts at the Teachers Insurance and Annuity Association – College Retirement Equity Fund (TIAA-CREF), a large provider of retirement services for employees at nonprofit institutions.\(^6\) In their sample, one-third of individuals who took distributions in 2008 suspended their distributions the following year. Extrapolating this figure to the general population, the authors estimate that the RMD suspension caused a 20\% reduction in taxable distributions from 403(b)s in 2009.\(^7\)

To study the effects of the RMD rules on IRA decumulation, we create a nationally-representative panel data set of individuals ages 60 and older from 1999 to 2014 using Internal Revenue Service tax data, including information returns filed by fiduciaries, linked with data from the Social Security Administration. These data offer several advantages over other datasets that have been used to study decumulation behavior. First, our data have sufficient mass – representing 5\% of the population, or approximately 2.6 million observations per year – to allow for analyses of narrowly defined age groups. This is important because the decumulation behavior of younger retirees may be different from that of older retirees, regardless of the rules. In addi-

\(^5\)One major limitation of our study is that we do not observe consumption or total savings in the tax data. Therefore, we cannot speak directly to the effect of decumulation policy on consumption. However, we do observe non-IRA sources of income and discuss the differential withdrawal behavior among individuals who vary along this dimension.

\(^6\)Specifically, they study withdrawals from 403(b) plans, which provide tax advantages similar to IRAs and are available for public education organizations, cooperative hospital service organizations, self-employed ministers, and many other nonprofit employers in the United States. As noted by Brown et al., their sample is not nationally representative; TIAA-CREF plan participants tend to have larger accounts than the national average.

\(^7\)Several of the noted studies have explored decumulation from retirement savings accounts using survey or tax data. However, the studies that use tax return data are primarily descriptive, while those that use data from household surveys generally have small sample sizes and are unable to differentiate between traditional IRAs, which are subject to RMD rules, and Roth IRAs, which are not.
tion, RMDs vary by age and younger retirees may respond to the rules differently than older retirees. Second, administrative tax data are subject to less measurement error than survey data, particularly in the case of information provided by third parties. Third, we have a complete view of an individual’s traditional IRA balances and distributions across all fiduciaries. Fourth, we incorporate information from the tax data regarding non-IRA sources of income, marital status, and geographic location.

An important determinant of retirees’ welfare is their consumption, which is financed by savings, Social Security, defined benefit pensions, and transfers from government and family. Assets, inclusive of home equity and IRA balances, account for approximately one third of lifetime income for individuals who are near retirement age and represent one of the major sources of retiree consumption (Gustman and Steinmeier, 1999; Scholz et al., 2006; Love et al., 2009). Thirty years ago employer-provided defined benefit plans were a substantial source of retirement saving. Today, personal retirement accounts, including IRAs and 401(k)s, are the primary form of retirement saving for private-sector workers (Poterba et al., 2013; Holden and Bass, 2014).

We make several contributions to understanding IRA decumulation. First, we provide descriptive evidence of trends in the characteristics and behavior of retirement-age IRA account holders from 2000 through 2013. Second, we use the 2009 suspension of RMD rules to identify their causal effects on distributions across age groups. Third, we uncover an undocumented response to the rules: individuals who turn 70.5 and become subject to the rules exhibit an increased likelihood of closing their IRA accounts. Finally, we provide suggestive evidence of optimization frictions in retirees’ financial decisions, as many retirees continue taking distributions at the phantom RMD – the RMD they would have faced – when the rules were suspended in 2009.
Figures 3.2 and 3.3 visually capture many of the effects of the RMD rules on distribution behavior. First, the RMD rules affect individuals in non-suspension years. From 2008 to 2010, approximately one quarter of IRA-holders between the ages of 60 and 70 took a distribution, with an average distribution of 6.2% of the account balance, and with no statistically significant difference in 2009. In 2008 and 2010, the proportion taking a distribution increased to around 90% for 70.5-year olds, with their average distribution increasing to 10.9% of the account balance. Older retirees take larger distributions on average, with an overall mean among all individuals subject to the RMD rules of 13.1% of account balances. Second, the suspension of the RMD rules in 2009 caused a response among those who would have been subject to them. That year, only 40% of 70.5-year-old IRA-holders took a distribution, with an average distribution of 8.2% of account balances. These are significantly smaller than the comparable averages from 2008 and 2010. Older retirees are similarly less likely to take distributions. However, in 2009 the decumulation behavior of IRA-holders ages 70.5 or older remained different from the decumulation behavior of 60- to 70-year-olds. In particular, the proportion of 70.5-year-olds who take a distribution is roughly 32% larger than the proportion of younger individuals with distributions. This large, discrete jump in the likelihood of taking distributions suggests there may be optimization frictions associated with responding to (the suspension of) the RMD rules.

In a simple two-period model, we derive a parameter that reflects the proportion of IRA-holders who are RMD-constrained – that is, the proportion who would prefer to draw down their savings accounts less quickly than the RMD rules require. We implement two empirical strategies to identify this parameter and to more generally explore the effects of RMD rules on withdrawal behavior. Our first empirical strategy is based on two regression specifications. We first present results from reduced-form
regressions that identify the elasticity of IRA distributions with respect to the RMD. In an alternative first-differences specification, we estimate the effect of an unexpected change in the RMD on changes in distributions.

Our second empirical strategy employs the method developed by DiNardo et al. (1996) to construct the counterfactual density of IRA distributions that would have occurred had the rules not been suspended. We do this separately for each age group from 73 to 85 years of age, identifying the proportion of RMD-constrained individuals in each group. Crucially, the DiNardo et al. technique allows us to control for the effects of time-varying characteristics associated with distribution behavior – e.g. account balances and alternative sources of income – that changed in 2009 for reasons unrelated to the suspension of RMD rules. This is especially important, as the rules were suspended during the Great Recession.

Both estimation strategies produce robust evidence that RMD rules have large effects on decumulation behavior. Results from our second estimation strategy suggest that approximately 41% of individuals subject to RMD rules would prefer to withdraw less than their RMD, with the percentage increasing in age. Around 13% of individuals would prefer to withdraw nothing at all, though this percentage decreases in age, suggesting older retirees are more likely to desire a positive distribution less than the RMD. Consistent with Brown et al., 35% of individuals subject to the rules that took distributions in 2008 suspended their distributions in 2009, with the probability of suspension decreasing in age and increasing in account balance.

In 2009, approximately 20% of individuals made a withdrawal within half a percentage point of the distribution they would have been required to take. This is surprisingly large given that an individual’s optimal distribution is rarely equal to
the RMD, as discussed in Brown et al. (2014) and Sun and Webb (2012). The most likely explanation for the extra mass located at the phantom RMD in 2009 is the presence of optimization frictions: costs associated with deciding upon or adjusting IRA distributions. A growing literature analyzes the extent to which individuals face frictions in adjusting behavior to policy in a variety of settings, most frequently with respect to labor supply and taxable income (Chetty et al., 2009, 2011, 2013; Chetty, 2012; Kleven and Waseem, 2013; Gelber et al., 2015). In the context of IRA distributions, one plausible friction is the cost of paying attention. This explanation is consistent with Brown et al.’s evidence that many individuals did not know about (or remember) the 2009 suspension when asked about it five years later. Alternatively, if the gains from responding to the suspension are small, retirees who have planned their distribution path may not choose to re-optimize, consistent with the theory of Chetty (2012). Another plausible explanation is that retirees may perceive the rules as government-sanctioned financial advice. This, too, is consistent with Brown et al.’s survey evidence. To the extent there are optimization frictions or retirees perceive the rules as financial advice, the rules play an important role in determining distribution behavior beyond simply constraining distribution amounts.

The parameter estimates presented in this paper can be used directly to estimate the tax revenue consequences of proposed changes in IRA decumulation policy. In addition, they can be used to study the welfare implications of RMD rules and the optimal design of tax policy regarding retirement savings. These issues are increasingly important despite the relative dearth of attention they have received.

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8For example, in the context of the standard life-cycle model, setting consumption equal to the RMD is optimal when preferences are represented by log utility, the interest rate and the discount rate are equal to zero, and expected mortality is equal to that used by the IRS to construct the RMD schedule (Brown et al., 2014).
3.2 Conceptual Framework

In this section, we present a two-period model to characterize the effects of RMD rules on withdrawals from Traditional IRAs. We opt for a simple model, rather than the life-cycle models typically studied in the literature on retirement (e.g. Brown et al., 2015), because we do not observe many variables needed to estimate such a model, such as household consumption or the allocation of savings across non-IRA accounts. Moreover, life-cycle models do not yield closed-form analytical expressions that can be used in our empirical implementation. Here and in our empirical work we abstract away from the indirect effects of RMD rules, for example through the lifetime budget constraint, focusing on their contemporaneous effect on IRA distributions. We also abstract away from a more complicated portfolio decumulation problem with several asset types. Each of these abstractions are made for empirical tractability, not because the other features of retiree’s decision problems are uninteresting.

In our model, individuals live for two periods in retirement and they enter the first period with a Traditional IRA balance equal to \( B \). Each period they are endowed with exogenous income \( X_t \) (e.g. Social Security income), and in the first period they must

\[ \text{In the life-cycle setting, individuals maximize the expected discounted value of lifetime utility by choosing their consumption path in their retired years, given an endowment of wealth at the beginning of retirement, survival probabilities in each period, a discount rate, and an interest rate. In such models there are two ways RMD rules affect distribution decisions. The first is a direct effect: RMD rules in period } t \text{ constrain distribution decisions in period } t. \text{ The second is an indirect effect via the budget constraint. If an individual is forced to distribute more than they would prefer in period } t, \text{ this affects the account balance in later periods, which in turn may affect distribution decisions in any period, including periods prior to } t. \text{ Therefore, unless optimal consumption paths are unconstrained in all periods, RMD rules may affect the entire path of distributions, including distributions not subject to the rules.}

\[ \text{De Nardi et al. (2015), Webb et al. (2009), and Sun and Webb (2012) discuss in detail many of the considerations in devising an optimal decumulation path, for example, uncertain mortality and asset returns, rules of thumb (e.g. the 4% rule), uncertain end-of-life medical expenses, and bequest motives.} \]
take a distribution \( d \) from their IRA greater than or equal to the RMD \( \bar{d} \).\(^{11}\) The undistributed portion of the IRA from period one grows at a rate of \( 1 + r \), and the IRA balance in period two is fully distributed. Distributions in each period face a flat tax rate of \( \tau \).

Individuals choose \( d \geq \bar{d} \) to maximize the present discounted value of utility,

\[ u(c_1) + \beta u(c_2), \tag{3.1} \]

where \( u(\cdot) \) is a smooth, concave function, \( \beta \in (0, 1] \) denotes the individual’s discount factor, and consumption in periods one and two is given by

\[
\begin{align*}
  c_1 &= X_1 + (1 - \tau)d \\
  c_2 &= X_2 + (1 - \tau)(1 + r)(B - d).
\end{align*} \tag{3.2}
\]

Similar to the extant literature, we do not explicitly study the effect of bequest motives on IRA distributions. To the extent that individuals prefer to maintain more of their savings in tax-preferred plans for bequest reasons, this is reflected empirically in the fraction of RMD-constrained individuals. As noted by Poterba et al. (2013) and De Nardi et al. (2015), U.S. retirees decumulate their assets more slowly than implied by the standard life-cycle model, especially high-income individuals. This may be because of bequest motives, or the risks that the elderly face, for example due to uncertain life expectancy and medical costs. Our empirical strategy allows us to remain agnostic about the determinants of optimal distributions, and the semiparametric estimation strategy that we present in Section 3.4 is robust to the underlying theory behind distribution decisions.

\(^{11}\)The simple theory presented here assumes full compliance with RMD rules and therefore abstracts away from penalties for non-compliance. In any given year, approximately 90% of individuals subject to the RMD rules comply. The 10% non-compliance rate attenuates our estimates for the fraction of RMD-constrained individuals and for the overall effect of RMDs on distributions towards zero.
In the first period there are two types of individuals: the constrained and the unconstrained with respect to the RMD rule. We refer to individuals who would prefer to take a distribution smaller than the RMD as the “RMD-constrained.” Letting $d^*(\bar{\delta})$ denote the optimal distribution given an RMD of $\bar{\delta}$, the RMD-constrained are those with $d^*(0) < \bar{d}$. Note that the fraction of individuals who are RMD-constrained will generally depend on the prevailing RMD. Thus, in the empirical portion of this paper, we focus on estimating the fraction of individuals who are RMD-constrained given current RMD policy.

Given the same required distribution $\bar{d}$, individuals may or may not find the RMD a binding constraint. The difference is generated by heterogeneity in other resources ($X$), tax rates ($\tau$), investment rates of return ($r$), discount factors ($\beta$), and utility ($u$). Let $\alpha_c(\bar{d})$ denote the fraction of RMD-constrained individuals given RMD policy $\bar{d}$. These individuals choose $d = \bar{d}$, however, not all individuals who choose $d = \bar{d}$ are RMD-constrained. Given a smooth distribution of the underlying fundamentals, some fraction of individuals will have $d^*(0) = \bar{d}$, and therefore will have $d^*(\bar{d}) = \bar{d}$. Thus we cannot distinguish between the RMD-constrained and the RMD-unconstrained based on observed distributions. In Section 3.4, we present two strategies for estimating the fraction $\alpha_c(\bar{d})$ using the 2009 RMD suspension for identification.\(^{12}\)

We are also interested in estimating the effect of eliminating RMD rules on the density of distributions. Figure 3.1 graphically illustrates this effect. Two densities of distributions are plotted. The density $f_0$ describes distributions, measured as a percent of the IRA account balance, absent any RMD. The density $f_1$ describes distributions,\(^{12}\)

\(^{12}\)To identify the fraction of RMD-constrained individuals under a range of potential RMD levels not observed in the data, we require policy variation that modifies, rather than suspends, RMD rules. In 2002, the entire RMD schedule was relaxed due to a change in the life expectancy tables used by the IRS. We plan to incorporate this policy change into our analysis to explore this issue further.
measured as a percent of the IRA account balance, given a positive RMD $\bar{d}$. Above $\bar{d}$ the two densities coincide, however, any individuals who choose $d < \bar{d}$ when there is no RMD must relocate, choosing $d = \bar{d}$ when facing the RMD. The individuals who relocate are the RMD-constrained, and their mass ($\alpha_c(\bar{d})$) is marked in the figure: it is precisely the mass near the RMD under $f_1$ less the mass near the RMD under $f_0$. For a given age group, we estimate this parameter using the actual 2009 density of distributions as the analog of $f_0$ and using the predicted counterfactual density in 2009 that would have occurred were the rules not suspended as the analog of $f_1$.\footnote{This estimation strategy, and the theory behind it, ignores the optimization frictions that kept some individuals’ distributions near the phantom RMD in 2009. In future work, we plan to address this shortcoming by measuring these frictions.}

Figure 3.1: Theoretical Effect of RMDs

The figure plots hypothetical densities of distributions from Traditional IRAs, both with and without the RMD constraint.
3.3 INSTITUTIONAL BACKGROUND AND DATA

Here we briefly describe the relevant features of IRAs, including their tax treatment. We then describe the nature of our data and present summary statistics on the population of individuals ages 60 or older.

3.3.1 INDIVIDUAL RETIREMENT ACCOUNTS AND DISTRIBUTION RULES

IRAs offer significant tax advantages to individuals saving for retirement. Several types of IRAs exist, but the vast majority of IRA funds are held in Traditional IRAs. We use the term “IRA” to refer specifically to Traditional, SEP and SIMPLE IRAs throughout the remainder of the paper. The primary benefit of IRAs is tax deferral. When contributed to an IRA, earned income is exempt from taxation until withdrawal, as are any investment returns that accumulate within an IRA account. Distributions from IRAs are taxed as ordinary income and are subject to required minimum distribution (RMD) rules. Employer-provided qualified retirement plans, such as 401(k)s, are also subject to RMD rules, however we do not study decumulation within these plans because we do not observe their account balances in the data.\textsuperscript{14} We also refrain from analyzing withdrawals from Roth IRAs, which are not subject to RMD rules because distributions from these accounts are tax-free.

RMD rules apply to an IRA-holder beginning the year in which she turns 70.5 years of age.\textsuperscript{15} However, the first year features a grace period: the first required distribution may be delayed until April 1 of the subsequent year. This allows the taxpayer to avoid

\textsuperscript{14}Qualified retirement plans include tax-qualified plans described in section 401 of the Internal Revenue Code, employee retirement annuities described in section 403(a), tax-sheltered annuities described in section 403(b), and a plan for government employees described in section 457(b).

\textsuperscript{15}See Warshawsky (1998) for a thorough discussion of the historical development and intent of the rules.
penalties in the event that she becomes aware of the rules during tax-filing season. For IRAs and defined-contribution plans, the RMD for each year generally is determined by dividing the account balance as of the end of the prior year by an applicable age-specific factor in the Uniform Lifetime Table of IRS Publication 590. This schedule is depicted in Figure 3.5. It begins at age 70.5 with an RMD of approximately 3.7% of account balances, and rises gradually to approximately 8.0% by age 90. This leaves 30% of the original account balance intact by age 90 even if investments generate zero returns.

A different RMD schedule is used for married individuals whose spouses are more than ten years younger than they are. These individuals follow the Joint Life and Last Survivor Expectancy Table, which specifies a smaller RMD. We incorporate this variation in RMDs for our regression analysis, but when employing the technique of DiNardo et al. (1996) we limit our sample of married individuals to those with spousal age differences of 10 years or less. This restriction is unlikely to bias our estimates as it results in few observations being dropped – only 3.4% of married individuals – and our regression analysis suggests that RMD rules do not have different effects on the distributions of individuals with marital age differences greater than ten years.

Inherited IRAs are subject to a separate set of RMD rules. Beneficiaries who are not spouses and who elect to treat the inherited IRA as their own may opt to treat the IRA according to the inheritance-specific RMD rules or to take distributions according to the alternative five-year rule. Under the five-year rule, the entire account must be distributed by the end of the fifth year following the previous owner’s death and no distribution is required for any year before the fifth year. However, we

\[16\] If an individual has multiple IRAs, the RMD is calculated by dividing the sum of account balances by the age-specific factor. It is satisfied if the sum of distributions exceeds this amount. Note that this means an individual could potentially distribute a sufficient amount from one account and leave the others untouched.
do not observe which treatment beneficiaries elect and cannot measure the amount distributed relative to the RMD (because some beneficiaries do not have an RMD). \(^\text{17}\)

Fiduciaries that serve as trustees of IRAs are required to inform account holders if the RMD rules apply to them and the date by which their required distribution must be taken. In addition, they must either specify the amount of the RMD or offer to calculate it. If an individual does not make a withdrawal that is at least as large as their RMD, the penalty is a 50-percent excise tax on the undistributed required amount. The tax is generally imposed during the taxable year in which the distribution was required. Thus, a taxpayer who discovers in March that he did not satisfy the prior year’s RMD should use Form 5329 to calculate the excise tax penalty and report this amount on his tax return for the prior year. \(^\text{18}\)

While RMD rules have always been related to a measure of average remaining life expectancy, the RMD schedule has changed occasionally. In 2002, the entire schedule shifted down: conditional on age, owners were required to make smaller distributions measured as a fraction of their account balance compared to previous years. This was because of an increase in the average life expectancies used by the IRS. The effect of the schedule change can be seen in Figure 3.5.

Under the provision entitled “Pension Provisions Relating to Economic Crisis” of the Worker, Retiree, and Employer Recovery Act of 2008, individuals were not required to make a distribution for calendar year 2009 from individual retirement plans or employer-provided defined-contribution retirement plans. While there is no official explanation for the 2009 RMD suspension, we believe it was implemented

\(^{17}\)Five percent of individuals take an inheritance-related distribution annually. We plan to explore inheritance-related distributions in future work.

\(^{18}\)The IRS may waive the penalty if the failure to satisfy the RMD was due to reasonable error and steps were taken to remedy the violation.
because of decreasing account balances associated with the Great Recession. In 2010, the RMD rules were once again in effect.

3.3.2 Nationally Representative 5% Random Sample

Prior to Brown et al. (2014) – hereafter, “BPR” – few studies rigorously analyzed the extent to which RMD rules affect IRA distributions, largely due to data constraints. The administrative tax data we use are well-suited to explore the effects of RMD rules on IRA distribution behavior for several reasons. First, the data have sufficient sample size to construct smooth distributions for individual age groups. Second, tax data suffer from a lesser degree of measurement error than most survey data. Third, these data allow us to construct a complete profile of individuals’ IRAs, as opposed to being limited to a single fiduciary. Finally, tax data include a variety of information on income (including other asset-based income), household structure, and geographic location, and can be organized as a panel.

The primary set of data used in this study is a 5% random sample drawn from the population of individuals in the United States with an identification number recorded by the Social Security Administration (SSA) who are not known to be deceased by SSA. Our sampling method is based on an administrative identifier called a “masked taxpayer identification number” (TIN). The IRS randomly generates this number for every individual with a date of birth recorded by the Social Security Administration. We draw our sample by limiting our analysis to observations with certain TIN endings.

The base sample – hereafter, the “5% Sample” – is limited to individuals aged 60 and older from 1999 to 2014. An observation is an individual-year combination. We impose the following sample restrictions. First, individuals with no tax returns or information returns in any year are dropped. This restriction results in roughly 350,000 individuals being dropped, though many of these individuals are
likely deceased. The sample remains representative of the national population despite this restriction, as Cilke (2014) finds that 99.5% of the Census resident population had information filed with the IRS in 2011 and that this proportion is roughly constant across birth-year cohorts. Second, observations are dropped if the individual dies in the current year or the following year.\textsuperscript{19} This restriction causes our sample to under-count the resident population, but reduces the effect of end-of-life decisions on our empirical estimates.

The data are organized as a panel, with roughly 37 million person-year observations. The panel is balanced for individuals alive and 60 or older in every year of our sample, and is unbalanced for those who die or age into our sample during the sampling period. We prefer this sampling structure to a purely balanced panel, as the data better approximate the U.S. population age 60 or older in every year, with younger individuals aging in to replace those leaving the panel. We supplement these data with information from the Social Security Administration on dates of birth and death, as well as sex at the time of birth.

Information returns are individual-specific and are typically filed by third parties, such as fiduciaries or employers. We use the following information returns: Form 5498 (contributions to retirement savings accounts), Form 1099-R (distributions from pensions and retirement savings accounts), Form 1099-SSA (Social Security benefits), Form W-2 (wages and 401(k) contributions), Form 8606 (Roth conversions), Form 1099-INT (interest income), Form 1099-DIV (dividend income), and Form 5329 (penalties for failure to take a RMD). From these we observe IRA balances, contributions, distributions, and other income information. Individuals may receive multiple information returns of a given type – because they have multiple jobs or multiple IRAs – and we collapse the data to one observation per individual-year, summing\textsuperscript{19} Approximately 31% of individuals die during the 16-year sample period.
and counting relevant variables. Importantly, these forms are not limited to those individuals appearing on a tax return, though most individuals who have an IRA also file a tax return.

Tax returns are Form 1040s, which are filed by tax units, a proxy for households. Multiple individuals may appear on a tax return as a primary or secondary filer or a dependent. From the Form 1040 we observe income information, including many items not reported on information returns such as business income, deductions and credits, and total income.

We make two additional restrictions to our base sample to construct our empirical sample. First, we limit the sample to the years 2000 through 2013. The RMD of an individual is based on the fair-market value of their IRA account balance at the end of the previous year, as reported by their fiduciary on Form 5498. As discussed previously, an individual calculates their RMD by multiplying their account balance in the previous year by the RMD percentage that is relevant for them (e.g. 5%). We cannot measure individual-specific RMDs in 1999 because we do not have Form 5498 data in 1998. We exclude 2014 from our analysis due to concerns that not all returns have been filed at this time. Second, we exclude observations in the top 1% of distributions measured as a percentage of the previous year’s account balance (more than 103%). Many of these distributions are implausibly large, and are likely data errors.

For the bulk of our empirical analysis, we create a separate sample further limited to individuals who have a positive IRA balance in at least one year. We refer to this as the IRA Holders Sample. Note that a person-year observation in the IRA Holders Sample may or may not have a positive IRA balance in that year. We also refer to
the RMD Sample, which is the subset of individuals in the IRA Holders Sample aged 70.5 or older with a positive RMD for the observation year (including 2009).20

3.3.3 Summary Statistics

Table 3.1 presents a variety of summary statistics for the 5% sample. This sample contains 37.58 million individual-year observations for the years 2000 through 2013. Seventy-three percent of individuals appear on a Form 1040 as a primary or secondary filer, 36% have a Form 5498 filed on their behalf, and 54% receive a 1099-R.21 Further, 29% have a Form 1099-DIV, 55% have a Form 1099-INT, and 28% have a Form W-2. A negligible proportion file Form 5329, which indicates a failure to satisfy the RMD.

We observe marital status only for individuals filing a tax return. Conditional on filing, 67% of individuals in the sample are married. However, 27% of observations are associated with a non-filing individual in a given year. For these observations, we impute marital status and spousal age difference as follows. If an individual filed a tax return in a previous or later year, we use their marital status (and spousal age difference) from the nearest year, provided that the spouse is still alive in the current year. If the spouse has died by the current year, we do not impute a marital status for that year. Using the imputed marital status variable, we find that 61% of individuals in the sample are married. We do not have an imputed marital status for the 8.7%

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20 We make two small additional timing-related restrictions in our construction of the RMD Sample. First, we exclude individuals in their second year of being subject to RMD rules for the year 2000. That is, we exclude individuals who turn 71 during 2000 if their birth month is January-June and individuals who turn 72 during 2000 if their birth month is July-December. We do this because we cannot determine whether these individuals satisfied their first-year RMD in 1999. Second, we exclude individuals who are first subject to RMD rules in 2013 because we cannot determine whether they satisfy their first RMD by April 2014, as the 2014 data are incomplete.

21 The 1099-R/5498 discrepancy comes from the fact that Form 5498 is filed for IRAs only, while Form 1099-R is for distributions from IRAs, pensions, annuities, and life insurance contracts. Therefore, if an individual receives a distribution from a defined benefit pension and does not have an IRA, they will receive a Form 1099-R but not a Form 5498.
of individuals who fail to file a tax return in any sampled year. Instead, we calculate their RMD based on the Uniform Lifetime Table, which is the RMD schedule used for over 96% of observations for which we know the marital status and spousal age difference from the Form 1040.\textsuperscript{22}

Over 35% of individuals in the 5% sample have an IRA. The average size of an IRA is $151,604 in inflation-adjusted 2014 dollars and there is substantial variation in balance sizes, with the distribution of IRA balances exhibiting a long right tail. We focus on distributions from IRAs categorized as “normal distributions.” We define a normal distribution as a distribution from a traditional IRA that could be used to satisfy the RMD rules, regardless of whether an individual is subject to the RMD rules. A normal distribution does not include distributions that are associated with rollovers, Roth conversions, recharacterizations, disability or inheritance-related distributions, distributions from a Designated Roth account, or those from IRAs that have been structured to have annuity payments. In our sample, 19% of individuals make a “normal distribution” and the average annual size of normal distributions is $12,991, or about 15% of the previous years’ account balance.\textsuperscript{23}

Four percent of individuals have a total distribution, which is the distribution prior to an account closure. Specifically, we define a total distribution as the annual distribution associated with the year before a year in which an individual ceases to have a positive account balance.\textsuperscript{24} The average size of total distributions is $46,972.

\textsuperscript{22}When we exclude non-filers from the sample for the regression specifications discussed in Section 3.4, we get slightly smaller effects associated with the RMD. This is likely because non-filers tend to be lower income individuals and it may be that the rules are more binding for them.

\textsuperscript{23}The sample size varies slightly for the two variables because the size of a distribution measured as a percentage of the account balance requires that we observe the size of the account in the previous year, whereas the levels variable does not.

\textsuperscript{24}Form 1099-R has a box that indicates a total distribution. However, because many people have multiple accounts, we define total distributions as described above to measure a true extensive margin instead of account consolidation.
Table 3.2 shows summary statistics for the IRA Holders and RMD samples—the latter is a subset of the former: those IRA holders required to take a minimum distribution. The average RMD in 2014 dollars is $5,893, approximately 5% of the IRA balance. The size of the average normal distribution is 15% of account balances for the entire sample and 12% among individuals in the RMD Sample. Among individuals in their 70.5 year, over 84% take their first RMD in their 70.5 year, instead of postponing to the following year. This is potentially for tax-smoothing reasons: if an individual chooses to postpone their first RMD to their second year, they are responsible for taking both their first and second RMDs in that year and both are included in taxable income.

Ninety-one percent of individuals take a normal distribution that satisfies their RMD, which suggests the rules are binding for the majority of RMD-relevant individuals. Among individuals who fail to satisfy their RMD, only 0.54% file a Form 5329 for the purpose of paying the excise tax penalty associated with an excess accumulation in an IRA account. It is unclear if the non-compliance is due to deliberate tax evasion or simply forgetfulness or confusion on the part of the individuals that comprise our sample. Figure 3.7 suggests it is likely the latter, as the average percentage of individuals that satisfy their RMD is above 90% until age 85, after which it declines substantially with increasing age. Furthermore, individuals in their first two years of being subject to the rules are slightly more likely (less than one full percentage point) to satisfy their RMD relative to older individuals. It does not appear there are many repeat non-compliers: for any two year combination, only 2-3% of individuals do not comply in both years.

These data reveal the increasing importance of IRAs as a savings vehicle for older Americans. The percentage of individuals age 60 or older in the United States with a Traditional IRA steadily increased from 29% in 2000 to 35% 2013, as shown in Figure
3.8. The percentage with Roth IRAs increased by a similar magnitude, from around 0% in 2000 to 7% in 2013. The amount of assets held in IRAs grew significantly over this time period. Assets held in Traditional IRAs – shown in Figure 3.9 – more than doubled since 2000, increasing from $1.9 trillion to approximately $3.8 trillion in 2013 (in inflation-adjusted 2014 dollars). The amount of assets held in Roth IRAs also increased substantially relative to 2000 levels, but remains a small fraction of Traditional IRA assets.

The Great Recession was associated with a substantial drop in assets in 2009 – account balances are measured at the beginning of the calendar year – but by 2011 assets exceeded their 2008 levels. Average account balances – displayed in 3.10, along with quartile measures – also fluctuated with the Great Recession, but only recently regained their inflation adjusted 2008 levels. The pattern for the 75th percentile of account balances was similar. Median account balances, on the other hand, rebounded relatively quicker. Figure 3.10 is indicative of the substantial right-skewness of the distribution of balances: the mean is close to the 75th percentile, and exceeds it for most sample years. The same is true of the distribution of normal distribution sizes, displayed in Figure 3.11.

Normal distributions also decreased in 2009. Distributions conditional on taking a distribution, however, do not show a dip analogous those in account balances and asset totals. This can been seen in Figure 3.12, as the trend for mean distributions is flat through the Great Recession and the RMD suspension in 2009. Coupled with Figure 3.11, this suggests two similar responses offset one another and resulted in conditional distributions levels remaining flat. First, many people with below average annual distribution amounts – for example, those taking distributions at the RMD threshold with average account balances – suspended their distributions in 2009. The
effect of their exit is to push the average up in 2009, ceteris paribus. This was offset by individuals reducing their distributions who nonetheless took positive distributions.

3.4 Empirical Methods and Evidence

In this section we discuss two strategies to identify the effect of the Required Minimum Distribution rules (RMD) on distributions from traditional IRAs: reduced-form regressions and the estimation of counterfactual densities of IRA distributions.

3.4.1 Graphical Evidence of the Effect of the 2009 RMD Suspension

In this section, we provide a discussion of the descriptive graphical evidence with regard to the effect of the 2009 RMD suspension on distributions. Figures 3.2 and 3.3 visually capture many of the effects of the RMD rules. It is clear the RMD rules affect individuals in non-suspension years. Approximately 25% of individuals younger than 70.5 took a distribution, with an average distribution of 6.2%, measured as a percent of the account balance withdrawn. The fraction of individuals who make a distribution increases linearly with age from 60 to 70. In non-2009 years, the proportion taking a distribution increases to over 90% for 70.5-year olds. The average size of a distribution jumps by 76% to 10.9% of the IRA account balance for 70.5-year olds, with a 13.1% average among all individuals subject to the RMD rules.

The fraction of individuals in 2009 with a distribution is only 60% among 70.5-year olds: the analogous rate in non-suspension years is 90%. The average distribution size fell by roughly 25% from 10.9% of the IRA account balance to 8.2%. However, the size of distributions in 2009 still represents a “new” 70.5 year olds relative to the distribution patterns of 70 year olds (who are not yet subject to the rules) and younger. Similarly, the proportion of individuals aged 70.5 with a distribution from
a traditional IRA in 2009 is roughly 32% larger than the proportion of younger individuals with distributions. This large, discrete jump in the proportion at age 70.5 – in a year where the RMD rules were suspended – suggests there may be optimization frictions associated with decumulation and the RMD rules.

Distribution patterns in 2009 also differ from 2008 and 2010 when examining those with non-zero distributions in Figure 3.4. Distribution levels as a percent of account balances are elevated for all ages in 2009, and are particularly elevated for those that would have been subject to RMD rules. This is because the level of distributions (conditional on taking a distribution) was flat from 2008 to 2010, as was discussed in the previous section and is shown in Figure 3.12. Holding the level of distributions constant (numerator) and reducing the size of the balance (denominator) results in larger distributions as a percentage of account balances.

Another interesting feature of Figure 3.3 is the local maxima in distribution sizes at age 70.5. This extra mass is entirely attributable to an increase in total distributions – distributions associated with closing an account – that occur at age 70.5, when individuals are first subject to the RMD rules. In fact, once we remove individuals who make total distributions the extra mass disappears.

Figure 3.17 and Figure 3.18 show the densities of IRA distributions among 73-, 75-, 80-, and 85-year olds from 2005-2008 and 2008-2009, respectively. Both Figures focus on distributions between zero and 15%, at the left tail of the distribution, as the tail to the right is long and flat (see Figure 3.16). The density for a particular age group is consistent across years other than 2009. In fact, the degree of consistency is such that it is difficult to visually differentiate between the density associated with different years.

In contrast, Figure 3.18 shows substantially different densities of IRA distributions among 73-, 75-, 80-, and 85-year olds in 2009 relative to 2008. The value of the RMD
according to the Uniform Lifetime Table is shown by the vertical line. For example, the RMD shown in panel (b), for 75-year olds, is 4.37% which applied to over 96% of 75-year olds in 2008. From this figure, there is clear evidence that the RMD compresses the lower tail of the density of IRA distributions across all age groups and suggests that a large proportion of individuals are RMD-constrained. Prior research shows that only for a very limited set of circumstances is the RMD an optimal distribution, and the extra mass at the non-existent RMD in 2009 is indicative of optimization frictions.

IRA distributions may have been different in 2009 regardless of the policy change because of macroeconomic factors, for example, declining housing values. However, the average size of distributions by age group and year shown in Figure 3.3 suggest that changing macroeconomic factors from 2008-2009 may not have a large effect on distribution behavior. Individuals younger than 70.5 were not affected by the 2009 RMD suspension and, therefore, the change in their average distributions in 2009 is a good approximation of the average effect of those macroeconomic factors on distributions for older individuals, assuming the macroeconomic factors affect the two age groups similarly. As Figure 3.3 clearly shows, average distributions for the younger, unaffected group did not change at all in 2009: they are extremely similar to those in 2008 and 2010. To explore this further, Figure 3.19 shows the distributions of IRA distributions, measured as a percent of the account balance in the previous year, among individuals ages 60-69 from 2008 to 2010. While similar, the 2009 distribution is not perfectly aligned with that of 2008 or 2010: individuals took slightly larger distributions in 2009 relative to 2008 or 2010, as evidenced by the lesser amount of mass in the left tail and shift to the right. This is likely, at least partly, due to the decline in account balances.
3.4.2 Reduced-Form Estimation

In Section 3.2, we present a comparative static that shows the effect of changes in the RMD on IRA distributions. In this section, we perform an analogous regression analysis on the individuals in our sample age 70.5 or older with a non-zero account balance (the RMD sample). The regression equation below shows the effects of changes in the RMD, measured as a percent of the previous year account balance, of individual \(i\) in period \(t\), \(RMD_{it}\), on IRA distributions, also measured as a percent of the previous year account balance, \(d_{it}\), in year \(t\):

\[
d_{it} = \alpha_0 + \alpha_1 i + \alpha_2 RMD_{it} + \alpha_3 X_{it} + \epsilon_{it}
\]

(3.3)

where \(\alpha_0\) are year fixed effects, \(\alpha_1\) are individual fixed effects, and \(X_{it}\) represents a vector of time-varying individual characteristics. Specifically, \(X_{it}\) includes variables that determine the individual’s RMD: age group dummy variables, marital status, and an indicator variable equal to 1 if an individual is more than 10 years older than their spouse and equal to 0 otherwise. In some specifications, we also include the natural log of the IRA account balance in the previous year. The year fixed effects control for any determinants of distributions that are common to all individuals, for example, due to macroeconomic conditions. The age group fixed effects control for any determinants that are common to all individuals within the same age group, for example, a decreased remaining life span.\(^{25}\) Individual fixed effects control for any unobserved, time-invariant heterogeneity in determinants of distributions, such as savings preferences, household resources, life expectancy deviations from age-specific averages, medical expense uncertainty, and attitudes toward risk. The \(\epsilon_{it}\) is an unobserved, additive error component that represents sampling error or unobserved, time-varying

\(^{25}\)We can include age fixed effects because not all individuals who are the same age have the same RMD.
heterogeneity at the individual-year level in determinants of IRA distributions. We allow for the errors to be correlated at the individual level.

The parameter of interest is the coefficient on $RMD$, $\alpha_2$, which represents the average effect of a one percent increase in the RMD on IRA distributions, measured as a percent of the account balance. As discussed in Section 3.2, if every individual who is subject to the RMD rules is RMD-constrained, that is, they would prefer to withdraw less than the required amount, this coefficient will be equal to one. Alternatively, if no one is RMD-constrained and every individual withdraws at least their required minimum, the coefficient will be zero. Variation in $RMD_{it}$ comes from within-individual, across-time variation in the RMD. The individual-level RMD is exogenous after controlling for the variables that determine it, which allows us to identify $\alpha_2$.

In our preferred specification, we measure the dependent variable and the RMD as the natural log of the level, instead of as percents. In this specification, $\alpha_2$ also represents an (average) elasticity: it measures the percentage change in IRA distributions due to a one percent change in the RMD. While point estimates from both specifications suggest a similar elasticity, around 0.6, we view the log specification as preferable because the relationship between IRA balance size and distributions is non-linear.

In general, $\alpha_2$ is not equal to $\alpha_c$, the fraction of RMD-constrained individuals at the 2008 RMD levels, from Section 3.2 for two reasons. First, for the specification given in equation 3.3, we cannot include 2009 because we include year fixed effects and all individuals have an RMD equal to zero in 2009. Second, for the entire 2000-2013 empirical sample, there are similarly aged individuals subject to two separate RMD schedules: the 2000-2001 and the 2002-2014 schedules. We run the following
first-differences specification that enables us to include the large, unexpected changes in RMDs induced by the 2009 policy suspension:

\[
\Delta \ln(d_{it}) = \alpha_2 \Delta \ln(RMD_{it}) + \alpha_3 \Delta X_{it} + \mu_{it}
\] (3.4)

We include time and age-group fixed effects and changes in the covariates included in the previous specification. The coefficient \(\alpha_2\) measures the effect of an unexpected change in the RMD on distributions. Because the 2009 policy suspension did not go into effect until December 23, 2008 and, it is unlikely that distributions in 2008 were affected.

**Results**

Tables 3.3 and 3.4 show the regression results for equation 3.3 for the RMD Sample, excluding the year 2009 (the year of the RMD holiday). In our preferred specification, with the results shown in Table 3.4 Column (3), the estimated coefficient on the natural log of the RMD indicates that a 10% increase in the RMD causes a 5.82% increase in IRA distributions. The coefficient on the RMD is statistically significant at the 1 percent level across all specifications. The magnitudes of the estimates suggest that the RMD rules have a substantial effect on IRA distributions. While the estimated coefficient on marital status is inconsistent across specifications, it is often negative, which is consistent with married households having more resources in retirement than unmarried households. Surprisingly, individuals with spouses 10 or more years younger have larger distributions than singles or those with spouses closer in age. Finally, account size and distributions exhibit a sizable and strong relationship: the estimates in our preferred specification suggest that a 10% increase in IRA balance size is associated with a 33% increase in distributions. Because all of these non-RMD
covariates are likely endogenous, we cannot attribute causality to the estimated coefficients associated with them.

Table 3.5 shows the regression results for the first differences specification shown in equation 3.4. The first column presents the first differences estimates for all years, including 2009. The coefficient estimates are similar to those in the levels specification (Column 3 of Table 3.4) and show that a 10% increase in the RMD causes a 5.4% increase in distributions. Column 2 presents the results for all years excluding the change from 2008 to 2009, while Column 3 presents the results just for the change from 2008 to 2009. The estimates indicate that an unexpected change in the RMD has a larger effect (0.61) on distributions than an expected change in the RMD (0.49). In the last column, we present results from a specification that includes an interaction between the (change in the) natural log of the RMD and the (change in the) natural log of the IRA balance. As expected, the interaction term is negative: account holders who experienced larger increases in their balance between 2008 and 2009 were less responsive to the change in the RMD induced by the policy suspension than those who experience small (or negative) changes in their account balances.

3.4.3 **Counterfactual Densities of IRA Distributions**

The estimating equation discussed in the previous section is confined to studying the average effect of RMDs. In this section, we consider the effect of RMDs on the entire density of IRA distributions. To illustrate the importance of studying the entire density, Figure 3.17 and Figure 3.18 show the densities of IRA distributions among 73-, 75-, 80-, and 85-year olds from 2005-2008 and 2008-2009, respectively. In years other than 2009, the density for a particular age group is very consistent. In contrast, Figure 3.18 shows substantially different densities of IRA distributions among 73-, 75-, 80-, and 85-year olds in 2009 relative to 2008. The value of the RMD according
to the Uniform Lifetime Table is shown by the vertical line. For example, the RMD shown in panel (b), for 75-year olds, is 4.37% which applied to over 96% of 75-year olds with IRAs in 2008. The figure shows clear evidence that RMDs affect the lower tails of the densities of IRA distributions across all age groups. This suggests that a large proportion of individuals are RMD-constrained, which is consistent with the reduced-form results of the previous section.

Below, we discuss the procedure we use to estimate a counterfactual density of IRA distributions for each RMD-constrained age group in 2009. For example, consider unmarried 75-year olds (or those with spouses not more than 10 years younger): before and after 2009, these individuals faced an RMD of 4.37% of their account balance. We observe the actual distribution of IRA distributions for 75-year olds in 2008 and 75-year olds in 2009, as shown in panel (b) of Figure 3.18. However, the 75-year olds in 2009 did not have a required distribution and the mass at a distribution level of 0 increased. The purpose of the method presented here is to estimate the density of IRA distributions of 75-year olds in 2009 as if RMDs had not been suspended.

The observed 2008 distribution for 75-year olds is not a perfect counterfactual for that of 75-year olds in 2009 for 2 reasons. First, macroeconomic factors changed substantially and, therefore, the density for 75-year olds in 2009 may have been different from that of the same age group in 2008 independent of the RMD suspension. Second, 75-year olds in 2008 are not the same individuals as 75-year olds in 2009: if the characteristics associated with the density of IRA distributions for 75-year olds vary over time, the same age group from a different year is not a perfect comparison group.

To address these concerns, we use the method developed in DiNardo et al. (1996), referred to as “DFL", which was developed to estimate counterfactual wage densities associated with institutional features of the U.S. labor market, such as the minimum
wage or unionization rates. The method is well suited to a decomposition of changes in the distribution of IRA distributions in 2009 because it allows for us to separate the effect of time-varying characteristics associated with distribution behavior from the 2009 RMD suspension. The DFL method is a generalization of the Oaxaca-Blinder wage decomposition, which uses regression techniques to measure how the average wage of one group (e.g. women) would be different if they had the characteristics of another group (e.g. men). While the Oaxaca-Blinder method focuses on mean wages, the DFL method generalizes measurement to the entire wage distribution.

Our formal explanation of the method follows DFL. We use 75-year olds in 2008 and 2009 as an example, though in our empirical implementation we use the method for all RMD-constrained age groups and various years. We limit our analysis to individuals subject to RMDs given by the Uniform Lifetime Table so that we can hold constant the RMD – measured as a percent of account balance – for all similarly aged individuals.\(^{26}\)

Consider each observation in the pooled dataset as a vector \((d, z, t)\), where \(d\) is an IRA distribution measured as a percent of the IRA account balance, \(z\) contains individual characteristics, and \(t\) takes on one of two year values (2008 or 2009). Each individual observation belongs to the joint distribution \(F(d, z, t)\) of distributions, individual characteristics, and dates. The joint distribution of IRA distributions and characteristics at one point in time is the conditional distribution \(F(d, z|t)\). For a particular age group, this joint distribution may depend on distributional characteristics, such as the RMD measured as a percent of the account balance that must be withdrawn, \(RMD_t\). The density of IRA distributions at one point in time, \(f_t(d)\),

\(^{26}\)We omit the less than 4% of individuals subject to a different RMD schedule due to a spousal age gap of over 10 years. Their RMD schedule is not conducive to implementing the estimation methods presented here.
is written as the integral of the density of distributions conditional on a set of individual characteristics and date $t_d$, $f(d|z, t_d; RMD_t)$ over the distribution of individual characteristics $F(z|t_z)$ at date $t_z$:

$$f_t(d) = \int_z dF(d, z|t_{d,z} = t; RMD_t)$$
$$= \int_z f(d|z, t_d = t; RMD_t)dF(z|t_z = t)$$
$$\equiv f(d; t_d = t, t_z = t, RMD_t) \quad (3.5)$$

Therefore, while $f(d; t_d = 2009, t_z = 2009, RMD_{2009})$ represents the actual density of IRA distributions in 2009 among 75-year olds, $f(d; t_d = 2009, t_z = 2009, RMD_{2008})$ represents the density that would have prevailed in 2009 if the RMD of 75-year olds had been that of the 2008 cohort, keeping the individual characteristics of the 2009 75-year old cohort the same.

To construct the counterfactual density of interest $f(d; t_d = 2009, t_z = 2009, RMD_{2008})$, we need to make the following assumptions. First, we need to assume that the RMD has no spillover effects on the distribution of IRA distributions above the RMD. That is, for any two values $RMD_0$ and $RMD_1$ of the RMD with $RMD_0 \leq RMD_1$, the conditional densities $f(d|z, t_d; RMD_0)$ and $f(d|z, t_d; RMD_1)$ are the same for IRA distributions above the highest value of the RMD, which is $RMD_1$. Formally, this implies:

$$[1 - I(d \leq RMD_1)]f(d|z, t_d; RMD_0) = [1 - I(d \leq RMD_1)]f(d|z, t_d; RMD_1) \quad (3.6)$$

where $I(\cdot)$ is the indicator function. This assumption will be satisfied if individuals maximize their utility by choosing how much to withdraw from their IRA account, compare that amount to their RMD, and either distribute an amount equal to their
optimum or, in the case where their optimal distribution is less than the RMD, take their RMD. However, the assumption will be violated if individuals “target” their distribution according to the RMD. For example, if the schedule requires that an individual distribute 4.37% of their account and their decision rule is to withdraw this amount plus 2 percentage points the assumption will be violated. In Section 3.4.4, we provide empirical evidence that this assumption is satisfied. In our implementation, we use the RMD plus one percentage point to allow for rounding error.\footnote{We are conducting analysis to determine the optimal threshold value.}

The second assumption is that the shape of the conditional density of real IRA distributions at or below the RMD only depends on the value of the RMD. For two years, $t_0$ and $t_1$, and two values of the RMD, $RMD_0$ and $RMD_1$ with $RMD_0 \leq RMD_1$, the shape of the conditional density $f(d|z, t_0; RMD_1)$ that would prevail at $t_0$ if the RMD were $RMD_1$ is proportional to the shape of the conditional density $f(d|z, t_1; RMD_1)$ for IRA distributions at or below the highest value of the RMD, $RMD_1$. In other words, for IRA distributions that are at or below the value of the 2008 RMD, the conditional density of distributions that would prevail in 2009 if the RMD were at the 2008 level instead of equal to zero is proportional to the conditional density of IRA distributions in 2008. This implies:

\[
I(d \leq RMD_{2008})f(d|z, t_d = 2008; RMD_{2008}) = \psi_d(z, RMD_{2008})I(d \leq RMD_{2008})f(d|z, t_d = 2009; RMD_{2008})
\]  

(3.7)

where $\psi_d(\cdot)$ is a re-weighting function to be defined below. This assumption will be violated if the distribution behavior of individuals who do not comply with the
RMD rules changes over time. We find no empirical evidence that this assumption is violated: for example, the RMD compliance rate is relatively stable over time.\footnote{An exception is 2001, when there was a 4 percentage point decrease in the percentage of individuals who satisfy their RMD.}

Finally, the third assumption is that the RMD has no effect on the probability of having an IRA among individuals subject to RMD rules. This assumption rules out extensive margin effects of the RMD rules. Opening an account in response to RMD rules is unlikely to occur, as individuals subject to RMD rules are ineligible to open an account. Keeping open an account that would have otherwise been closed is also unlikely, as ceteris paribus RMD rules restrict IRA use. Closing an account in response to the rules, however, is potentially a concern. There is graphical evidence of a small increase in total distributions among 70.5 year olds. Because of this and timing issues associated with the RMD rules for 70.5-72 year olds, we do not use the DFL method to construct counterfactual densities for these age groups. In Section 3.4.5, we discuss this in more detail and provide empirical evidence that the assumption is reasonable for the older age groups.

We construct a 2009 conditional density with the RMD at its 2008 level by selecting the part of the 2009 density above $RMD_{2008}$ and the part of the 2008 density at or below $RMD_{2008}$ with an indicator function. To make sure the overall counterfactual density integrates to one, we pre-multiply the 2008 density by a re-weighting function $\psi_d(z, RMD_{2008})$. Formally, this implies:

$$f(d|z, t_d = 2009; RMD_{2008}) = I(d \leq RMD_{2008})\psi_d(z, RMD_{2008})f(d|z, t_d = 2008; RMD_{2008})$$

$$+ [1 - I(d \leq RMD_{2008})]f(d|z, t_d = 2008; RMD_{2008})$$

\[(3.8)\]
where the re-weighting function \( \psi_d(z, RMD_{2008}) = \frac{Pr(d \leq RMD_{2008}|z, t_d=2009)}{Pr(d \leq RMD_{2008}|z, t_d=2008)} \). To obtain the effect of the RMD on the overall distribution of IRA distributions in 2009, we integrate the conditional density given by equation 3.8 over the distribution of individual characteristics:

\[
f(d; t_d = 2009, t_z = 2009; RMD_{2008})
= \int f(d|z, t_d = 2009; RMD_{2008})dF(z|t_z = 2009)
= \int I(d \leq RMD_{2008})\psi_d(z, RMD_{2008})f(d|z, t_d = 2008; RMD_{2008})dF(z|t_z = 2009)
+ [1 - I(d \leq RMD_{2008})]f(d|z, t_d = 2008; RMD_{2008})dF(z|t_z = 2009)
= \int I(d \leq RMD_{2008})\psi_d(z, RMD_{2008})f(d|z, t_d = 2008; RMD_{2008})\psi_z(z)^{-1}dF(z|t_z = 2008)
+ [1 - I(d \leq RMD_{2008})]f(d|z, t_d = 2008; RMD_{2008})dF(z|t_z = 2009)
\]

(3.9)

where the re-weighting function \( \psi_z(z)^{-1} = \frac{Pr(t_z = 2009|z)}{Pr(t_z = 2008|z)} \cdot \frac{Pr(t_z = 2008)}{Pr(t_z = 2009)} \) and the product of the two re-weighting functions in equation 3.9 is given by:

\[
\psi(z, RMD_{2008}) \equiv \psi_d(z, RMD_{2008}) \cdot \psi_z(z)^{-1}
= \frac{Pr(t_d = 2009|z, d \leq RMD_{2008})}{Pr(t_d = 2008|z, d \leq RMD_{2008})} \cdot \frac{Pr(t_z = 2008)}{Pr(t_z = 2009)}
\]

(3.10)

In the DFL method, the two dates are viewed as possible events in the date space: therefore, the unconditional probabilities in the above equation, \( Pr(t_z = 2008) \) and \( Pr(t_z = 2009) \), are equal to the number of observations in the respective year divided by the total number of observations in the pooled dataset. To measure the conditional probability terms, we estimate the probability of being at date \( t \), given certain individual characteristics and an IRA distribution below the 2008 RMD using a probit model.
\[ Pr(t_d = t|z, d \leq RMD_{2008}) = Pr(\epsilon > -\beta' H(z)) = 1 - \Phi(-\beta' H(z)) \tag{3.11} \]

where \( \Phi(\cdot) \) is the cumulative normal distribution and \( H(x) \) is a vector of covariates that is a function of \( x \). We construct the vector \( H(x) \) to consist of: a gender dummy, imputed marital status, a quartic of the previous year account balance, Social Security benefits, wage income, taxable pension benefits, and income from interest, dividends, and capital gains.\(^{29}\) We estimate the probit model by pooling observations from 2008 and 2009 that have IRA distributions, measured as a percent of the account balance, smaller or equal to the 2008 RMD. In the empirical implementation, we use the RMD plus 1 percentage point (e.g. 5.37) because of the abnormal concentration of distributions just above the RMD (4.37), which suggests either small spillover effects or rounding. We discuss potential spillover effects in the next section.

**Results**

Figure 3.22 shows the 2009 actual and counterfactual densities using 2008 as the baseline year for four age groups: 73-, 75-, 80-, and 85-year olds. Each graph shows the actual density (the solid line) in contrast with the estimated counterfactual density (dotted line) that would have prevailed if the RMD rules had not been suspended in 2009, holding individual characteristics at 2009 levels. The age group-specific RMD level according to the Uniform Lifetime Table is represented by a vertical line, which increases across age groups. We limit the horizontal axis to distributions that are 15% of the account balance or less because this is where the differences between actual and counterfactual densities are located.\(^{30}\)

\(^{29}\)For a large subset of individuals in our sample, we also explored including the effect of median housing prices at the zip-code level. The results for the subsample with this inclusion are similar as to that for the entire sample without.

\(^{30}\)Approximately 85% of the total mass is included with the 15% cut-off.
Our graphical evidence suggests a large fraction of individuals are RMD-constrained across all age groups. The shift in mass from the age group-specific RMD to 0 is consistent with the 2009 RMD suspension inducing many individuals to suspend their distributions. Table 3.6 shows the difference in density between the 2009 actual and counterfactual densities (within half a percentage point) at two points: 0 and the level of the 2008 RMD, across all age groups. For example, among 73-year olds, 39% of individuals are RMD-constrained at the 2008 RMD level, with nearly 40% of them suspending distributions when not subject to the RMD rules, and the remainder taking distributions in 2009 between 0 and the 2008 RMD. As Figure 3.22 and Table 3.6 elucidate, there is heterogeneity in the difference in density at the RMD across age groups. In general, as individuals age, approximately the same proportion (41%) are RMD-constrained at current RMD levels. However, a smaller proportion prefer to suspend distributions completely and instead prefer to take a distribution between zero and the current RMD.

The difference in density at the RMD, 0.39 for 73-year olds, is an estimate of the proportion of RMD-constrained individuals $\alpha_c$ from Section 3.2 in a simple world with no inattention or inertia. However, all of the empirical evidence shows there is a substantial proportion of people in each age group who take a distribution very similar to the RMD they would have been subject to if the RMD suspension had not occurred. Figure 3.3 provides evidence of these potential optimization frictions. Individuals younger than 70.5 years take an average distribution of 6.2% in 2008-2010, with no statistically significant difference in 2009. In years other than 2009, the average distribution jumps by 76% to 10.9% for 70.5-year olds, with a 13.1% average among all individuals subject to the RMD rules. In contrast, in 2009, the average distribution among 70.5-year olds is 8.2%, which is a much smaller increase than in other years, but still a 32% increase. Similarly, the average distribution among
all individuals subject to the RMD rules is around 20% lower in 2009 compared to non-2009 years, at 10.4%. To explore this issue further, we calculate the proportion of individuals who made a withdrawal within half a percentage point of their RMD in 2009, shown in the last column of Table 3.6. Approximately 20% of individuals made such a withdrawal, a substantial fraction given that only for a very limited set of circumstances is the RMD an optimal distribution, as discussed in Brown et al. (2014) and Sun and Webb (2012). The fraction increases slightly with age.

The most likely explanation for the “extra” mass located at the phantom RMD in 2009 is inattention. In a survey of TIAA-CREF participants, Brown, Poterba, and Richardson (BPR) document that 45% of individuals either did not know about or did not remember the temporary suspension. In addition, BPR provide evidence suggesting a large fraction of retirees view the RMD rules as a form of financial planning advice from policymakers.\footnote{Specifically, they find that half of the 403(b) participants in their sample agreed that “...required minimum distribution [provide] ... some guidance on how much you can spend each year for the rest of your life without running out of money.”} In recent work, Gelber et al. (2015) document earnings adjustment frictions in response to changes in the Social Security Annual Earnings Test among U.S. retirees from 1983 to 1999.\footnote{Friedberg (2000) established that there was substantial bunching among Social Security beneficiaries and that the bunching shifts in response to changes in the earnings test kink.} They find that among this group of retirees, the fixed cost associated with adjustment is $280: if the gains associated with adjusting to policy changes exceed this level, then individuals adjust their earnings. In addition, bunching at old kink points dissipates by 3 years after the policy changes. While our sample is different from that of Gelber et al. (2015), our (suggestive) evidence of frictions is consistent with their findings. We expect that if the RMD rules were permanently removed, the mass at the pre-removal RMD would gradually disap-
pear. Because of the apparent optimization frictions, for example due to inattention, the difference in density at the RMD is a lower bound on $\alpha_c$ at existing RMD levels.\footnote{We are working to estimate a frictionless measure of $\alpha_c$.}

The densities presented in Figure 3.22 use 2008 as the baseline year from which the 2009 counterfactual densities are estimated. However, 2008 may not be a good control year because macroeconomic factors associated with the Great Recession that could affect distribution behavior were shifting.\footnote{Figure 3.17 suggests that individuals not subject to the rules did not take substantially different distributions in 2009 relative to 2008, which is also supported in Poterba et al. (2013).} Therefore, we also construct counterfactual densities using 2006, 2007, 2010 and 2011 as the baseline. The results for 75-year olds are shown in Figure 3.23. Estimates of the counterfactual density is robust across baseline years, with larger mass at the RMD for 2010 compared to 2006, 2007 and 2011.

As discussed in the previous section, the DFL method is sensitive to the empirical threshold value used as the RMD.\footnote{This is a common issue that needs to be addressed when using the DFL method. DFL use the log of $3.00$ instead of the log of the actual (1979) minimum wage of $2.90$ because of spillovers, for example due to rounding error.} In Figure 3.24, we show counterfactual densities with 2008 as the baseline year and varying RMD threshold values. To generate the baseline graphs presented above, we use a threshold value of 1: that is, for an RMD value equal to 4.37, we use a value of 5.37 ($1 + 4.37$) as the point below which the counterfactual is estimated. As Figure 3.24 shows, a threshold value of 0 generates a counterfactual density with too little mass immediately to the right of the actual RMD. Threshold values of 0.5-0.63 provide a smoother counterfactual. In our main specifications, we use a threshold value of 1 to allow for RMD spillovers further in the distribution. The empirical cost associated with increasing the threshold value is
that a larger portion of the counterfactual density is estimated, as opposed to using the actual density in 2009.

In our first-differences specification shown in equation 3.4, we find an average RMD elasticity of 0.6. In a context with perfect compliance and for the special case where the difference is measured from 2008 to 2009 exclusively, the coefficient on $\alpha_2$ is equal to $\alpha_c$ and measures the (average) fraction of individuals who are RMD-constrained at current RMD levels. Using the DFL estimation strategy, the (weighted) average of the fraction of individuals who are RMD-constrained at current levels is 0.41. To further explore why these estimates from the two strategies differ, we present results from a regression of equation 3.4 for a subset of the original regression sample: we create a DFL-comparable sample that is limited to individuals aged 73 - 85 who are subject to the Uniform Lifetime RMD schedule. In addition, because of imperfect compliance, we limit the regression sample to individuals who complied in 2008, i.e. those who took a distribution at least as large as their RMD. The results are shown in Table 3.7. The coefficient on the (change in) the natural log of the RMD is 0.437 and more in line with the DFL estimates of the fraction of RMD-constrained among individuals ages 73-85. The difference between the estimated elasticity for the DFL-comparable sample and the entire sample is likely due to heterogeneous responses among individuals between the ages of 70.5 and 72, older than 85, and the imperfect compliers.

3.4.4 Determinants of 2009 RMD Suspension

In this section, we discuss the characteristics of individuals who suspended distributions in 2009. We define "suspenders" as individuals who: (1) had a positive IRA balance at the end of 2008, (2) did not take a distribution in 2009, and (3) took a
normal distribution in 2008. Under this definition, 35% of individuals are suspenders in 2009 – very similar to the findings of BPR.

First, we examine suspenders’ 2008 IRA distributions. In Section 3.2, we hypothesize that only people constrained by the RMD rules at the pre-2009 levels will suspend their distributions in 2009.\footnote{Several other hypotheses are consistent with suspension, including beliefs that asset valuations were temporarily depressed in 2009.} Here, we test whether suspenders appear to be RMD-constrained in the previous year. Figure 3.25 shows graphs of the 2008 densities for 73-, 75-, 80-, and 85-year olds. Individuals in the “Everyone” category had a positive IRA balance at the end of 2008. The graphs are consistent with our hypothesis: compared to everyone, suspenders are much more likely to have been taking exactly their RMD in 2008. Figure 3.26 shows the analogous 2008 distributions for all individuals who did not take a 2009 distribution: that is, this includes suspenders and individuals who did not take a distribution in 2008. In 2009, 37.4% of individuals did not take a distribution, which includes individuals who may be non-compliers. Ignoring non-compliers would likely lead to an overestimate of the intensive margin effect, as non-compliers likely did not suspend their distributions in 2009 due to the policy and would have taken a zero distribution regardless.

We find that 65% of individuals in 2008 choose distributions amounts within 1 percentage point of their RMD. The probability of suspending in 2009, conditional on having a 2008 distribution that is within one percentage point of the RMD, is 41.1%. However, the probability of suspending in 2009 conditional on having a 2008 distribution that is more than one percentage point larger than the RMD is 16.6%. While Brown et al. find a small difference in the probability of suspending between these two groups, our results suggest that “suspenders” in 2009 are precisely those we expect to suspend: the RMD-constrained. Figure 3.25 provides visual evidence of this
difference: the suspension probability is clearly decreasing in the difference between the previous years’ distribution and RMD.

Next, we run probit regressions with the dependent variable as an indicator variable for being a 2009 suspender, similar to those in BPR. We include the following regressors: age group dummy variables, gender, marital status, the natural log of IRA balance in 2008, and the difference between the 2008 distribution and RMD, both measured as a percent of account balance. 3.8 displays the marginal effects from 2 specifications, one without and one with the last regressor: the difference between the 2008 distribution and RMD. Similar to BPR, we find the probability of suspension declines with age: the marginal effect is negative and statistically significant for all age groups older than the 70.5-74 group (the omitted group). In addition, we find that women and married individuals were more likely to suspend, and the suspension probability is increasing in the 2008 account balance. While BPR also find that married individuals were more likely to suspend, they find that men were more likely to suspend.

The first assumption of DFL is that there are no spillover effects of the RMD for IRA distributions above the RMD. While we cannot test this assumption directly, the evidence presented in this section provides strong support for the assumption. Individuals who take a distribution equal to or less than their RMD when required – and who suspend distributions when offered the opportunity – are likely influenced by RMD rules. If Figure 3.25 instead showed that most suspenders had 2008 distributions well above their RMD, we would view that as evidence in violation of the assumption.

3.4.5 Effect of the RMD on Total Distributions

The third DFL assumption is that the RMD has no effect on the probability of having an IRA among the individuals subject to the RMD rules. This assumption rules out
extensive margin effects of the RMD rules. In essence, we assume that the (suspension of the) RMD rules do not induce individuals to close their IRAs. Given that the policy change we use for identification is a suspension, the relevant question is whether some individuals who would have taken a total distribution in 2008, and thus not been a part of our sample in 2009, instead chose to keep their IRAs because of the policy. However, the timing of the policy precludes violation of this assumption.

The policy was signed into law December 23, 2008 as part of the Worker, Retiree, and Employer Recovery Act of 2008. Because of the timing associated with the policy, namely that it occurred at the end of the year, it is highly unlikely that individuals who otherwise would have closed their accounts chose not to because of the policy at the end of 2008. Empirically, we do not see a decrease in the proportion of individuals who take a total distribution in 2008.37

We observe an effect of the RMD rules on the probability of taking a total distribution for 70.5-year olds. Figures 3.3 and 3.2 show the average size of total distributions and the percent that take total distributions by age group, respectively, for 2008-2010. The average size of distributions increases at age 70.5 by nearly 5 percentage points before decreasing slightly and eventually increasing for ages 74 and older. The extra “bump” at age 70.5 shown in Figure 3.3 is attributable to an increase in total distributions that occur at age 70.5 when individuals are first subject to the RMD rules. This is also shown in Figure 3.2. Figure 3.21 displays the average size of distributions across age groups after removing individual-year observations in which the individual makes a total distribution.

The year in which an individual turns 70.5 is the first year that they are subject to the RMD rules. Because there is a cost associated with complying with the rules,

37This may be partly attributable to market conditions, as individuals would not want to sell off all of their assets when the value of those assets is low.
it may be that compliance costs for the marginal individual induces account closure. Figure 3.15 shows the average size of total distributions by age group. Among individuals who make a total distribution, the average size of the distribution declines substantially at age 70.5. This suggests individuals with smaller accounts are less willing to incur the cost associated with complying. In fact, Figure 3.15 shows that in 2009 when the cost of complying was zero, there is a smaller increase in the percent of 70.5-year olds with a total distribution relative to other years. Surprisingly, there is no offsetting increase in total distributions in 2010 among the individuals in their first year of being subject to the RMD rules in 2009.

3.4.6 WHO TAKES DISTRIBUTIONS NEAR THE RMD THRESHOLD?

We expect the income profiles of those with IRA distributions near the RMD threshold to systematically differ from those with IRA distributions exceeding the thresholds. In particular, we expect individuals taking distributions near the minimum to have higher incomes, for two reasons. First, individuals with less non-IRA income sources may need to draw down their IRAs for consumption. Second, individuals may engage in tax-smoothing, whereby they take IRA distributions – taxed at ordinary income rates – during low-tax years.

Table 3.9 compares average and median income values, along with traditional IRA balances, for those near the RMD threshold (i.e. within 0.5 percentage points in absolute value) and those in excess of the threshold. As expected, individuals with distributions near the RMD threshold have higher adjusted gross incomes on average (and at the median), despite having lower taxable IRA distributions. This holds for all non-IRA distribution sub-types of income we analyzed – interest, dividends, business, Social Security, and pensions – except capital gains. It also holds for both single and married tax units.
Next, we analyze patterns over time at the individual level. That is, we make use of the panel aspects of our data, and compare income amounts in years where an individual takes distributions near the RMD threshold to years their distributions exceed the threshold. We expect the former to be larger than the latter, to the extent individuals are tax smoothing or need to consume out of their IRA in low-income years. However, after limiting the sample to those individuals with distributions near their RMD threshold in at least one year, we find no discernible difference between the two.

3.5 DISCUSSION

Traditional IRAs are an increasingly important vehicle for retirement savings. From 2000 to 2013, the percentage of Americans age 60 or older with an IRA increased from 29% to 35%. The same time period saw a doubling in the real wealth held in IRAs by these individuals, from $1.9 trillion in 2000 to $3.8 trillion in 2013 (both measured in 2014 dollars). While there is a large literature that studies the effect of retirement savings policies on contributions to retirement savings accounts, relatively few studies have analyzed the effect of decumulation policies on withdrawals from these accounts. In order to make recommendations with regard to optimal retirement savings policy, research is required on the effect of current policy on saving and consumption during both working-age and retirement-age years. In this paper, we inform the latter.

We examine the effects of the Required Minimum Distribution (RMD) rules – which affect IRAs, 401(k)s, and similar plans – on distributions from IRAs. To study these effects, we use a 16-year panel of administrative tax data that contains information on taxpayer IRAs and distributions. We exploit the 2009 suspension of RMD rules to identify their effect on distributions across age groups. We find that the rules
have a large effect; we estimate that 41% of individuals would prefer to take an IRA distribution less than their required minimum. Using the semiparametric procedure developed by DiNardo, Fortin, and Lemieux (1996), we estimate the counterfactual density of IRA distributions that would have prevailed in 2009 if the rules had not been suspended. This allows us to separate the effect of time-varying characteristics associated with distribution behavior from the 2009 RMD suspension.

In addition to studying the distributional effects of the rules, we discuss the characteristics of those who suspended their distributions in 2009. We also document an extensive margin effect among individuals newly subject to the rules. Immediately upon aging into the population affected by RMD rules, retirees exhibit a higher probability of emptying their accounts. We also provide evidence suggestive of optimization frictions in retiree’s financial decisions. When the RMD rules were suspended, a large fraction of individuals withdrew an amount equal to the phantom RMD they would have been subject to if the rules were not suspended. A future goal of this research project is to theoretically model and empirically estimate the magnitude of these frictions. Note that distributions near the phantom RMD could also plausibly be explained by retirees taking the RMD schedule as a form of officially-sanctioned advice. Research elsewhere suggests a significant fraction of individuals indeed take this view (Brown et al., 2014).

Our analysis is focused on decumulation of Traditional IRAs because these assets represent a large fraction of overall wealth, are subject to RMD rules, and have account balance and distribution information reported to the IRS. Other types of retirement accounts, such as 401(k)s and Roth IRAs, do not share all of these features, nor do ordinary savings accounts or non-retirement investment accounts. However, many retirees face a simultaneous decumulation problem with several options for financing consumption. A full theoretical and empirical treatment of such a problem
is beyond the scope of this paper, but future research on this issue may yield further insights into the effects of RMD policy on the dis-savings decisions of retirees.
Table 3.1: Summary Statistics for Entire 5% Sample, 2000-2013

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>Max</th>
<th>Observations (Millions)</th>
</tr>
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<td>37.58</td>
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<td>0</td>
<td>1</td>
<td>37.58</td>
</tr>
<tr>
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<td>0</td>
<td>1</td>
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<td>0</td>
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</tr>
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<td>1</td>
<td>37.58</td>
</tr>
<tr>
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<td>0</td>
<td>1</td>
<td>37.58</td>
</tr>
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</tr>
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<td>0</td>
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<td>34.06</td>
</tr>
<tr>
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<td>0</td>
<td>1</td>
<td>37.58</td>
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<tr>
<td>IRA Balance Size</td>
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<td>*</td>
<td>13.16</td>
</tr>
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<td>*</td>
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<td>1</td>
<td>37.58</td>
</tr>
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</tr>
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<td>0</td>
<td>1</td>
<td>37.58</td>
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</table>

Summary statistics for the 5% sample, drawn from the universe of tax and information returns, representative of the population of individuals age 60 and older for the years 2000 through 2013. We exclude observations in the top 1% of distributions measured as a percent of the previous year’s account balance (more than 103%). We also exclude the tax year observations of individuals who die in the current year, a previous year, or the following year. Finally, we exclude individuals who have no tax or information returns in any year during our sample period. Dollar figures are presented in inflation-adjusted 2014 dollars.

*Omitted to protect taxpayer privacy.
<table>
<thead>
<tr>
<th>Variable</th>
<th>IRA Holders Sample Mean</th>
<th>Observations (Millions)</th>
<th>RMD Sample Mean</th>
<th>Observations (Millions)</th>
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<td>Normal Distribution Indicator</td>
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<td>Normal Distribution as % of Balance</td>
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<td>6.93</td>
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<td>0.91</td>
<td>0.55</td>
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</table>

The IRA Holders Sample is the subsample of individuals in the 5% sample who have a positive IRA account balance in at least one year during the 15-year sample period (1999-2014). The RMD Sample is the subset of individuals in the IRA Holders Sample age 70.5 or older and have a positive RMD for the observation year. The RMD Sample excludes individuals in their second year of being RMD-constrained for the year 2000 and individuals in their first year of being RMD-constrained for the year 2013. Dollar figures are presented in inflation-adjusted 2014 dollars.
Table 3.3: Effect of RMD on Distribution as % of Balance

<table>
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<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
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<td>RMD as % of Balance</td>
<td>0.425*</td>
<td>0.506**</td>
<td>0.536**</td>
</tr>
<tr>
<td></td>
<td>(0.169)</td>
<td>(0.170)</td>
<td>(0.166)</td>
</tr>
<tr>
<td>More than 10 years older than</td>
<td>0.008**</td>
<td>0.004</td>
<td>0.023***</td>
</tr>
<tr>
<td>spouse</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>First Year of RMD</td>
<td>-0.012***</td>
<td>-0.012***</td>
<td>-0.012***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Second Year of RMD</td>
<td>-0.000</td>
<td>-0.000</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Married</td>
<td>0.007***</td>
<td>-0.023***</td>
<td>-0.053***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>IRA Balance (Natural Log)</td>
<td></td>
<td></td>
<td>-0.053***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

Individual fixed effects regressions controlling for the variables that determine an individual’s RMD (age, year, first and second RMD year, and spousal age difference) and the natural log of the previous year account balance from which the RMD percentage applies. The dependent variable is IRA distribution measured as a percent of the previous year account balance. The married variable is binary, and includes both observed and imputed marital statuses. The sample includes all years from 2000 to 2013, excluding 2009. Standard errors are clustered at the individual level.
Table 3.4: Effect of RMD on Distributions - Natural Log Specification

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural Log of RMD</td>
<td>0.275***</td>
<td>0.265***</td>
<td>0.582***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.123)</td>
</tr>
<tr>
<td>More than 10 years older than spouse</td>
<td>0.046</td>
<td>0.319***</td>
<td>0.175***</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.033)</td>
<td>(0.042)</td>
</tr>
<tr>
<td>First Year of RMD</td>
<td>-0.394***</td>
<td>-0.396***</td>
<td>-0.402***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Second Year of RMD</td>
<td>0.027***</td>
<td>0.025***</td>
<td>0.018**</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Married</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IRA Balance (Natural Log)</td>
<td></td>
<td></td>
<td>0.335**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.123)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Year FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Age Group FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>N</td>
<td>5.39 Million</td>
<td>5.32 Million</td>
<td>5.27 Million</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.039</td>
<td>0.04</td>
<td>0.084</td>
</tr>
</tbody>
</table>

Individual fixed effects regressions controlling for the variables that determine an individual’s RMD (age, year, first and second RMD year, and spousal age difference) and the natural log of the previous year account balance from which the RMD applies. The dependent variable is the natural log of IRA distributions. The married variable is binary, and includes both observed and imputed marital statuses. The sample includes all years from 2000 to 2013, excluding 2009. Standard errors are clustered at the individual level.
Table 3.5: Effect of RMD on Distributions - First Difference Specifications

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>∆ Natural Log of RMD</td>
<td>0.542***</td>
<td>0.494***</td>
<td>0.608***</td>
<td>0.580***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>∆ Natural Log of IRA Balance</td>
<td>0.791***</td>
<td>0.784***</td>
<td>1.142***</td>
<td>0.436***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.016)</td>
<td>(0.061)</td>
</tr>
<tr>
<td>∆ More than 10 years older than spouse</td>
<td>0.028</td>
<td>0.076</td>
<td>-0.712**</td>
<td>-0.710**</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.043)</td>
<td>(0.250)</td>
<td>(0.250)</td>
</tr>
<tr>
<td>∆ Married</td>
<td>0.192***</td>
<td>0.181***</td>
<td>0.265***</td>
<td>0.270***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.048)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>Interaction: ∆ Natural Log of RMD and ∆ Natural Log of IRA Balance</td>
<td></td>
<td></td>
<td>-0.101***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.009)</td>
<td></td>
</tr>
</tbody>
</table>

Year FE       X       X       
Age Group FE  X       X       
N             4.81 Million 4.4 Million 409,980 409,980
R²            0.216   0.163   0.071   0.071

First differences regressions controlling for changes in the variables that determine an individual’s RMD (age, and spousal age difference) and the natural log of the previous year account balance from which the RMD applies. The dependent variable is the change in the natural log of IRA distributions. The married variable includes both observed and imputed marital statuses. The sample years for the regression results in column (1) includes all years from 2000 to 2013. The sample years for the regression results shown in column (2) includes all years from 2000 to 2013, excluding 2009. The sample year for the regression results shown in columns (3) and (4) is 2009. Standard errors are clustered at the individual level.
Table 3.6: Difference between 2009 Actual and Counterfactual Densities

<table>
<thead>
<tr>
<th>Baseline Year</th>
<th>Age</th>
<th>Difference in Density at Zero</th>
<th>Difference in Density at RMD</th>
<th>2009 Density at RMD</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>73</td>
<td>+0.15</td>
<td>-0.39</td>
<td>0.18</td>
</tr>
<tr>
<td>2008</td>
<td>74</td>
<td>+0.14</td>
<td>-0.39</td>
<td>0.19</td>
</tr>
<tr>
<td>2008</td>
<td>75</td>
<td>+0.14</td>
<td>-0.41</td>
<td>0.20</td>
</tr>
<tr>
<td>2008</td>
<td>76</td>
<td>+0.13</td>
<td>-0.42</td>
<td>0.19</td>
</tr>
<tr>
<td>2008</td>
<td>77</td>
<td>+0.14</td>
<td>-0.40</td>
<td>0.22</td>
</tr>
<tr>
<td>2008</td>
<td>78</td>
<td>+0.13</td>
<td>-0.40</td>
<td>0.22</td>
</tr>
<tr>
<td>2008</td>
<td>79</td>
<td>+0.12</td>
<td>-0.42</td>
<td>0.21</td>
</tr>
<tr>
<td>2008</td>
<td>80</td>
<td>+0.11</td>
<td>-0.41</td>
<td>0.19</td>
</tr>
<tr>
<td>2008</td>
<td>81</td>
<td>+0.11</td>
<td>-0.41</td>
<td>0.21</td>
</tr>
<tr>
<td>2008</td>
<td>82</td>
<td>+0.11</td>
<td>-0.41</td>
<td>0.22</td>
</tr>
<tr>
<td>2008</td>
<td>83</td>
<td>+0.10</td>
<td>-0.42</td>
<td>0.21</td>
</tr>
<tr>
<td>2008</td>
<td>84</td>
<td>+0.09</td>
<td>-0.41</td>
<td>0.21</td>
</tr>
<tr>
<td>2008</td>
<td>85</td>
<td>+0.08</td>
<td>-0.42</td>
<td>0.21</td>
</tr>
</tbody>
</table>

The table shows the difference in density between the 2009 actual and counterfactual densities, as estimated using the DFL method, at two points in the density of IRA distributions: zero and at the level the 2008 RMD. The density is calculated within half a percentage point of each point. To estimate the counterfactual densities, 2008 is used as the baseline year. The last column shows the 2009 density within half a percentage point of the RMD. Results are shown by age group, from age 73 to 85.
Table 3.7: Robustness First Difference Specifications

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>∆ Natural Log of RMD</td>
<td>0.437****</td>
<td>(0.007)</td>
</tr>
<tr>
<td>∆ Natural Log of IRA Balance</td>
<td>0.924***</td>
<td>(0.019)</td>
</tr>
<tr>
<td>∆ Married</td>
<td>0.444***</td>
<td>(0.073)</td>
</tr>
<tr>
<td>Year FE</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Age Group FE</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>149,155</td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.040</td>
<td></td>
</tr>
</tbody>
</table>

First differences regressions controlling for changes in the variables that determine an individual’s RMD (age) and the natural log of the previous year account balance from which the RMD applies. The dependent variable is the change in the natural log of IRA distributions. The married variable includes both observed and imputed marital statuses. The sample year for the regression results is 2009 and the sample is limited to individuals who: are age 73 or older, subject to the Uniform Lifetime RMD schedule, took a distribution at least as large as their RMD in 2008, do not have distributions measured as a percent of the previous year account balance in the top 1%. Standard errors are clustered at the individual level.
Table 3.8: Determinants of RMD Suspension Probability

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age 75-79</td>
<td>-0.075***</td>
<td>-0.015***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Age 80-84</td>
<td>-0.081***</td>
<td>-0.019***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Age 85-89</td>
<td>-0.08***</td>
<td>-0.014***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Age 90+</td>
<td>-0.044***</td>
<td>0.028***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Female</td>
<td>0.029***</td>
<td>0.024***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Married</td>
<td>0.074***</td>
<td>0.072***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>2008 IRA Balance (Natural Log)</td>
<td>0.018***</td>
<td>0.022***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>2008 Distribution - RMD (Percent)</td>
<td>-0.002***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000)</td>
</tr>
<tr>
<td>Observations</td>
<td>425,000</td>
<td>380,000</td>
</tr>
</tbody>
</table>

The table shows marginal effects from probit regressions where the dependent variable is an indicator equal to 1 if the individual had a positive distribution in 2008 and took a zero distribution in 2009, and equal to 0 if the individual took a distribution in 2009. The married variable is binary, and includes both observed and imputed marital statuses. Probit results are the marginal effects evaluated at the mean. The excluded age group is Age 70.5-74. Standard errors are in parentheses.
Table 3.9: Comparing Tax Units with Distributions Near and Beyond the RMD Threshold

<table>
<thead>
<tr>
<th></th>
<th>Near RMD Threshold</th>
<th>Beyond RMD Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Single</td>
<td>Married</td>
</tr>
<tr>
<td>Adj. Gross Income</td>
<td>54,575</td>
<td>104,056</td>
</tr>
<tr>
<td></td>
<td>[32,499]</td>
<td>[64,392]</td>
</tr>
<tr>
<td>Business Income</td>
<td>4,082</td>
<td>10,032</td>
</tr>
<tr>
<td></td>
<td>[0]</td>
<td>[0]</td>
</tr>
<tr>
<td>Social Security</td>
<td>16,949</td>
<td>28,585</td>
</tr>
<tr>
<td></td>
<td>[17,070]</td>
<td>[28,375]</td>
</tr>
<tr>
<td>Capital Gains</td>
<td>-2,903</td>
<td>1,118</td>
</tr>
<tr>
<td></td>
<td>[0]</td>
<td>[0]</td>
</tr>
<tr>
<td>Interest and Dividends</td>
<td>15,131</td>
<td>22,970</td>
</tr>
<tr>
<td></td>
<td>[4,929]</td>
<td>[6,732]</td>
</tr>
<tr>
<td>Taxable Pensions</td>
<td>15,590</td>
<td>25,128</td>
</tr>
<tr>
<td></td>
<td>[8,830]</td>
<td>[16,758]</td>
</tr>
<tr>
<td>Taxable IRA Dist.</td>
<td>7,012</td>
<td>13,132</td>
</tr>
<tr>
<td></td>
<td>[2,619]</td>
<td>[5,186]</td>
</tr>
<tr>
<td>AGI — Taxable IRAs</td>
<td>47,563</td>
<td>90,924</td>
</tr>
<tr>
<td></td>
<td>[27,349]</td>
<td>[53,617]</td>
</tr>
<tr>
<td>Trad. IRA Balances</td>
<td>135,990</td>
<td>152,670</td>
</tr>
<tr>
<td></td>
<td>[51,478]</td>
<td>[46,870]</td>
</tr>
<tr>
<td>Observations</td>
<td>842,548</td>
<td>1,573,963</td>
</tr>
</tbody>
</table>

Averages are presented, with median in brackets below. Comparison is limited to those filing Form 1040 with a positive normal IRA distribution. “Near” the RMD threshold is defined as being within 0.5 percentage points of the threshold in absolute value. Tax year 2009 is excluded as RMD rules were suspended in that year. Business income is comprised of gross profit or loss reported on Form 1040 Schedules C, E, and F. Interest and dividends include taxable and tax-exempt interest, and ordinary and qualified dividends. Social Security is taken from Form 1099-SSA, and represents gross retirement benefits. Capital gains are the sum of short-term and long-term capital gains from Schedule D. All dollar amounts are adjusted to 2014 levels.
The figure shows the percentage of individuals, among those with a positive Traditional IRA balance at the end of the previous year, who take a distribution from their Traditional IRAs. The underlying data are derived from a five percent random sample of individuals with Traditional IRAs.
Figure 3.3: Average Normal Distributions from Traditional IRAs (2008-2010)

The figure shows the average size of normal distributions from Traditional IRAs, measured as a percentage of the account balance at the beginning of the year, by age group from 2008 to 2010. The underlying data are derived from a five percent random sample of individuals with Traditional IRAs and are limited to those with a positive Traditional IRA balance at the beginning of the year. Note that individuals who took zero distributions are included in the calculations.
Figure 3.4: Average Normal Distributions from Traditional IRAs, Conditional on a Positive Distribution (2008-2010)

The figure shows the average size of distributions from Traditional IRAs, measured as a percentage of the account balance at the beginning of the year, by age group from 2008 to 2010. The underlying data are derived from a five percent random sample of individuals with Traditional IRAs and are limited to those with a positive Traditional IRA balance at the beginning of the year. Note that individuals who took zero distributions are excluded from the calculations.
The figure shows the Required Minimum Distribution (RMD), measured as the percentage of the IRA account balance that must be withdrawn, for ages 70 to 100 for the years 1999-2014. The schedule changed in 2002. Note that the schedule did not apply in 2009, as the RMD rules were temporarily suspended.
The figure displays statistics on Required Minimum Distributions from 2000 to 2013, excluding 2009 (when the RMD rules were suspended). The underlying data are derived from a five percent random sample of individuals subject to RMD rules. Dollars are adjusted to 2014 levels.
Figure 3.7: Percent of Individuals that Satisfy the RMD (2000-2013)

The figure shows the percentage of individuals who satisfy their RMD by age group during 2000 to 2013. The underlying data are derived from a five percent random sample of individuals with Traditional IRAs who are subject to the RMD rules.
Figure 3.8: Percentage of Individuals Ages 60 and Older with an IRA

The figure shows the percentage of individuals ages 60 and older with a positive balance in Traditional and Roth IRAs from 2000 to 2013. Note that some individuals have both types of accounts. The underlying data are derived from a five percent random sample of individuals who have a tax form reported to the IRS at some point during 1999 to 2014.
The figure shows the estimated amount of assets held in IRAs by the population of individuals ages 60 and older. The underlying data are derived from a five percent random sample of individuals from 2000 to 2013. Dollars are adjusted to 2014 levels.
Figure 3.10: Balances of Traditional IRAs Held by Individuals Ages 60 and Older

The figure displays statistics on Traditional IRA balances among individuals ages 60 and older who have a nonzero Traditional IRA balance. The underlying data are derived from a five percent random sample of individuals from 2000 to 2013. Dollars are adjusted to 2014 levels.
Figure 3.11: Normal Distributions from Traditional IRAs

The figure displays statistics on normal distributions from Traditional IRAs among individuals ages 60 and older who have a nonzero Traditional IRA balance. The underlying data are derived from a five percent random sample of individuals from 2000 to 2013. Dollars are adjusted to 2014 levels.
The figure displays statistics on normal distributions from Traditional IRAs among individuals ages 60 and older who take a nonzero normal distribution from a Traditional IRA. The underlying data are derived from a five percent random sample of individuals from 2000 to 2013. Dollars are adjusted to 2014 levels.
The figure shows the percentage of individuals with a nonzero Traditional IRA balance that take a total distribution. Total distributions represent individuals withdrawing all assets from their IRAs. The underlying data are derived from a five percent random sample of individuals from 2008 to 2010.
The figure displays statistics on total distributions – those distributions which take their IRA balances to zero – from Traditional IRAs among individuals ages 60 and older who take a total distribution from a Traditional IRA. The underlying data are derived from a five percent random sample of individuals from 2000 to 2013. Dollars are adjusted to 2014 levels.
The figure displays statistics on total distributions from Traditional IRAs. The underlying data are derived from a five percent random sample of individuals who take a total distribution from their Traditional IRA during 2000 to 2013.
Figure 3.16: Normal Distributions for Different Age Groups (2005-2008)

(a) 73-Year Olds

(b) 75-Year Olds

(c) 80-Year Olds

(d) 85-Year Olds

The figure shows the densities of normal distributions taken by 73-, 75-, 80-, and 85-year olds from their Traditional IRAs. The vertical line represents the RMD associated with the Uniform Lifetime Table. The underlying data are derived from a five percent random sample of individuals subject to RMD rules from 2005 to 2008. The top one percent of distributions (measured as a percentage of balances) have been dropped. Note that the same information is presented in Figure 3.17, except there is truncated to only show distributions less than or equal to 15% of IRA balances.
The figure shows the densities of normal distributions taken by 73-, 75-, 80-, and 85-year olds from their Traditional IRAs. The vertical line represents the RMD associated with the Uniform Lifetime Table. The underlying data are derived from a five percent random sample of individuals subject to RMD rules from 2005 to 2008. The top one percent of distributions (measured as a percentage of balances) have been dropped. Note that this figure is the same as Figure 3.16, except it is truncated to only show distributions less than or equal to 15% of IRA balances.
The figure shows the densities of normal distributions taken by 73-, 75-, 80-, and 85-year olds from their Traditional IRAs. The vertical line represents the RMD associated with the Uniform Lifetime Table. The underlying data are derived from a five percent random sample of individuals subject to RMD rules from 2005 to 2008. The top one percent of distributions (measured as a percentage of balances) have been dropped. Note that in 2009 the RMD rules were temporarily suspended.
Figure 3.19: IRA Distributions for Individuals Ages 60 to 69, Conditional on a Positive Distribution (2008-2010)

The figure shows the densities of Traditional IRA distributions, measured as a percent of the account balance in the previous year, among individuals ages 60 to 69 who take a positive distributions during 2008 to 2010. The underlying data are derived from a five percent random sample of individuals with a nonzero Traditional IRA balance at the beginning of the year.
Figure 3.20: Average Normal Distributions and RMDs (2000-2013, excluding 2009)

The figure shows the average size of normal distributions and Required Minimum Distributions, measured as a percentage of the account balance at the end of the previous year, from years 2000 to 2013 excluding 2009. The underlying data are derived from a five percent random sample of individuals with a nonzero Traditional IRA balance at the beginning of the year. Figure 3.21 displays the same information for those individuals that do not take total distributions.
The figure shows the average size of normal distributions and Required Minimum Distributions, measured as a percentage of the account balance at the end of the previous year, from years 2000 to 2013 excluding 2009. The underlying data are derived from a five percent random sample of individuals with a nonzero Traditional IRA balance at the beginning of the year who do not take total distributions. Figure 3.20 displays the same information but includes those individuals that take total distributions.
Panels show 2009 actual and counterfactual densities of IRA distributions for the following age groups: 73, 75, 80, and 85. The counterfactual densities are estimated using the methods described in DiNardo et al. (1996) and the baseline year used to estimate the counterfactual densities is 2008. The horizontal axis is limited to distributions, measured as a percent of the account balance, that are 15 or less.
Panels show 2009 actual and counterfactual densities of IRA distributions for 75-year olds. The counterfactual densities are estimated using the methods described in DiNardo et al. (1996) and the baseline years used to estimate the counterfactual densities are 2006, 2007, 2010, and 2011. The horizontal axis is limited to distributions, measured as a percent of the account balance, that are 15 or less.
Panels show 2009 actual and counterfactual densities of IRA distributions for 75-year olds. The counterfactual densities are estimated using the methods described in DiNardo et al. (1996) and the baseline year used to estimate the counterfactual densities is 2008. The RMD threshold is the difference between the actual RMD and the value used empirically. The horizontal axis is limited to distributions, measured as a percent of the account balance, that are 15 or less.
Panels show 2008 actual densities of IRA distributions across everyone and individuals who had a positive distribution in 2008 and took a zero distribution in 2009 for the following age groups: 73, 75, 80, and 85. The horizontal axis is limited to distributions, measured as a percent of the account balance, that are 15 or less.
Panels show 2008 actual densities of IRA distributions across everyone and individuals who took a zero distribution in 2009 for the following age groups: 73, 75, 80, and 85. The horizontal axis is limited to distributions, measured as a percent of the account balance, that are 15 or less.


Appendices

Appendix A: Bunching Robustness Checks

Here we test our estimation technique for sensitivity to parameter choice. The three key parameters are binwidth and the sizes of the bunching window and bunching region. In Section 2.3.1, we label these parameters $\delta$, $W$, and $R$, respectively. Binwidth simply measures how finely the data are collapsed when performing the analysis. The bunching window defines the area within which we count the total number of bunchers. We assume bunching does not occur outside the bunching window. Finally, the bunching region defines the area outside the bunching window that we use when constructing the counterfactual distribution of income if there were no kink.

As an example, our default parameter values are $\delta = $100, $W = 10$, and $R = 35$. This implies a bunching window of $W \cdot \delta = $1,000 and a bunching region of $R \cdot \delta = $3,500 around the kink. In other words, we assume the distribution of income within $1,000 of the kink is affected by bunching, but that outside this threshold the distribution is unaffected by bunching. Moreover, we use the observed distribution of income between $1,000 and $3,500 away from the kink to estimate the counterfactual distribution of income if the kink did not exist.

Tables 2.5 and 2.6 test how these parameters affect our bunching coefficients for the four most responsive groups at the first EITC kink, using 2003 data. We choose this year as it is the most recent year in which self-employed, low-income taxpayers bunch only at the first EITC kink. Starting in 2004, we are constrained when choosing the size of the bunching region, as self-employed taxpayers bunch at the nearby second
EITC kink. We discuss this constraint in further detail in Section 2.3.1. By presenting 2003 estimates here, we avoid this issue and thus are able to test a wide range of parameter choices.

The results indicate our findings are generally robust to parameter choice. For example, our preferred estimate for the bunching coefficient of our most responsive group – single, self-employed individuals with one child – is 32.48. Binwidth choices of $50 or $250 lead to estimates of 32.48 and 33.82, with small standard errors. Changing the bunching region by $500 in either direction also has small effects, with alternative estimates of 31.80 and 34.26. The one parameter that has a large effect on the estimates is the choice of bunching window. In particular, choosing a bunching window of just $500 causes the bunching coefficient to fall to 22.62. However, this is not a sensible choice for the bunching window, as visual inspection of Figure 2.11 makes clear. The income distribution is clearly affected by bunching behavior beyond $500 on either side of the kink. Cutting the bunching window short thus has two effects. First, it does not count those bunchers who are more than $500 beyond the kink. Second, it includes those bunchers when estimating the counterfactual distributions of income, artificially inflating these distributions. Both effects decrease the estimated number of bunchers and the corresponding observed elasticity.

Other groups show similar patterns. Our preferred bunching coefficient estimate for single, self-employed taxpayers with two children is 23.18. Except for the choice of bunching window, all other permutations leave the bunching coefficient in the range $[20.47, 26.06]$. Unsurprisingly, a smaller bunching window of $500 reduces the estimate to 13.20. Again, visual inspection of the distribution makes clear that it is still affected by bunching between $500 and $1,000 of the kink. For married, self-employed taxpayers, our preferred bunching coefficient estimates are 15.40 and 13.72, respectively, for those with one or two children. Except for the choice of bunching window, alterna-
tive estimates for these parameters lie in the ranges [15.37, 16.73] and [11.28, 15.56], respectively. For all cases, the bunching window could arguably be expanded from $1,000 to $1,500. This would generally increase our elasticity estimates. We take the conservative approach in choosing $1,000.
Appendix B: Bunching Analysis of Medicaid, SNAP, and Federal Disability Insurance

In this appendix we analyze whether federal income tax data provide evidence that individuals adjust their incomes to remain eligible for Medicaid, Supplemental Nutrition Assistance Program (SNAP), or federal disability benefits. These are large, economically important programs that serve millions of people. In 2011, there were approximately 57 million Medicaid participants, 45 million SNAP beneficiaries, and 8.5 million workers receiving federal disability benefits. We analyze these programs as a robustness check to ensure perceived bunching at kink points in the tax schedule was not caused by other incentives. We describe each program in broad strokes, with an emphasis on program-specific income definitions and eligibility thresholds. We then discuss our findings and conclude with a short discussion of the strengths and weaknesses of our approach. In short, we see no evidence of bunching associated with any of these programs, but this may be due to the limitations of the tax data in the context of these programs.

B.1 A Brief Description of Each Program

Medicaid provides health insurance at subsidized rates to low-income individuals, primarily parents, pregnant mothers, and children. For many, the program is free. Income eligibility criteria are a function of the federal poverty line, which is an increasing function of the number of adults and children in the household. Medicaid is administered at the state level, and the definitions of qualifying income and eligibility thresholds (as a percentage of the federal poverty line) vary by state. Importantly, during the period we analyze (2002 to 2011) Medicaid introduces a “notch” in the budget set, as earning income above the threshold results in a complete loss of benefits. This is
in contrast to having benefits phase-out, which would produce a kink. Given that the threshold is a notch and that Medicaid is a large benefit, we expect substantial responsiveness to this threshold.

SNAP provides funds to low-income individuals that can only be spent on certain types of food at participating retailers. Similar to Medicaid, it is a function of the federal poverty line, with larger households receiving greater benefits. Unlike Medicaid, the thresholds and income definitions do not vary across states, with the exceptions of Alaska and Hawai’i. Eligibility is limited to those with less than 130% of the federal poverty line in gross monthly income and less than 100% of the poverty line in net monthly income. Benefits begin phasing out with the first dollar of earned income. Individuals receive the difference between the maximum allotment per household (around $650 for a family of 4) and 30% of their monthly income. This produces a relatively modest non-convex kink at the end of the phase-out region.38

Federal disability insurance (DI) is administered by the Social Security Administration, providing monthly payments to individuals with a disability. Individuals must apply for DI and once approved are unable to earn income above a certain threshold without triggering a review of their claim or outright termination of benefits. Thus, the threshold (called the Substantial Gainful Activity threshold) is a notch. The Substantial Gainful Activity threshold ranged from $500 each month in 1996 to $1,000 each month in 2011. The size of the monthly benefit for DI recipients is a function of prior earnings and can range from a few hundred dollars to a few thousand dollars per month. As a result, we believe the potential for bunching to the left of this notch is substantial.39

38See www.fns.usda.gov/snap/eligibility for a thorough description of SNAP, including eligibility criteria and definitions of income.
39See www.ssa.gov/disability for a thorough description of federal disability insurance.
B.2 Qualifying Income and Kink Construction

SNAP and DI income eligibility thresholds are measured monthly, and in some states Medicaid income is measured monthly as well. Given that tax data record income on an annual basis, we construct the applicable kinks or notches by simply multiplying the monthly thresholds by twelve.\textsuperscript{40}

All three programs define income in an analogous manner to “earned income” qualifying for the EITC, but can include income items that are not recorded by the tax system, such as child support payments, housing subsidies, or Supplemental Security Income. In addition, various deductions are allowed and SNAP beneficiaries must satisfy the gross and net income tests described above. Medicaid income varies by state, but we use the same income definition for all states and all years.

We use the EITC sample as the basis for studying all three programs. These data are drawn with the following restrictions: all observations are from the seven states with no income taxes, all filed federal income tax returns, and all were between 25 and 65 years of age. We analyze Medicaid bunching from 2002 to 2011, SNAP bunching from 1996 to 2011, and DI bunching from 1999 to 2011.

B.3 Medicaid, SNAP, and Disability Insurance Bunching

We find an absence of bunching at each eligibility threshold in every state and every year. This is surprising given the value of these programs to participants – especially in the case of Medicaid and DI. The lack of bunching suggests either individuals are not adjusting their income in response to these programs, or our estimates are biased by substantial measurement error. Individuals might not respond if they have imperfect knowledge of income eligibility criteria, or because adjusting income is costly.

\textsuperscript{40}We retrieved annual state specific income eligibility thresholds for Medicaid from Foundation (2015).
On the other hand, individuals may be responding to these programs in ways that are undetectable with tax data. Federal income tax data do not contain all income or deduction items that comprise qualifying income for these programs. This is particularly relevant for the analysis of Medicaid, where the income definition varies across states and potentially over time. A second problem is that tax data are recorded annually, while eligibility for two (and in some states all three) programs are evaluated on a monthly basis. Thus, the only bunchers we can identify in our data for SNAP and DI are those that bunch in every month.
Appendix C: Exemption and Deduction Phase-outs

When determining taxable income, both personal exemptions and itemized deductions phase-out at high incomes, creating discontinuities in the budget constraints of high-income taxpayers. Our evidence suggests taxpayers do not respond to these incentives, but we describe them here for completeness. The phase-outs discussed in this section were in effect during our sample from 1996 to 2005, but were gradually removed beginning in 2006, with full removal from 2010 to 2012. They have since been reinstated.

The personal exemption phase-out (PEP) is a step function of AGI, generating notches in the budget constraint. Personal exemptions are reduced by 2% for each $2,500 of income exceeding the phase-out threshold until exemptions are exhausted. The beginning (and end) of the phase-out varies by filing status: $145,950 for singles, $182,450 for head of household, and $218,950 for married couples filing jointly in 2005.41

The itemized deduction phase-out (often referred to as “Pease” after former Ohio Congressman Donald Pease) reduces certain itemized deductions at a rate of 3 cents per dollar of AGI exceeding the threshold. However, Pease does not apply against itemized deductions generated from casualty and theft losses, investment interest, gambling losses, or medical expenses. The total percentage of itemized deductions eliminated by Pease is capped at 80% per taxpayer. Throughout the time period we study (1996-2005) this threshold is the same for all filing statuses except married couples filing separately, for whom the threshold is halved. In 2005 the threshold was $145,950 ($72,975), identical to the PEP threshold for singles.

41For all filers, the end of the phase-out region is $122,500 above the beginning.
Pease creates relatively small changes in marginal tax rates at its introduction and conclusion. For example, suppose a head of household with three children claims $20,000 of itemized deductions and earns exactly the Pease threshold of $145,950 in 2005. For a marginal increase of $1,000 above the Pease threshold, qualified itemized deductions are reduced by 3%, meaning the individual has 30 additional dollars of taxable income. If the taxpayer faces an initial marginal tax rate of 31%, she would see her marginal rate increase by around 1 percentage point ($30 \times 31% / $1000) as a result of Pease, creating a small convex kink. Similarly, once Pease is phased out the change is also around 1 percentage point, which creates a small non-convex kink. In the presence of moderate optimization frictions, these kinks are unlikely to induce a behavioral response.

PEP generates larger marginal tax rate increases than Pease. However, because the discontinuities PEP generates are notches, not kinks, assumptions are needed to calculate the magnitude of the discontinuity relative to a kink. For example, the “size” of a kink is calculated by dividing the difference between the net-of-tax rates (one minus the marginal tax rate) on either side of a kink, and dividing by the net-of-tax rate to the right of the kink. Calculating the size of a notch requires an assumption about the size of a marginal response by the taxpayer: do taxpayers adjust their income in $1, $50, or $1,000 increments?

Suppose a taxpayer earns income at the PEP threshold. She has four personal exemptions, which reduce taxable income by $4 \times $3,200 = $12,800. If this taxpayer earns at least 1 additional dollar but less than 2,500 additional dollars, her personal exemptions will be reduced by $256 (2% \times $12,800). Assuming her marginal tax rate is 31% initially, this increases her tax liability by $31\% \times $256 = $79.36. If we assume a marginal response constitutes a $1 change in income, the implicit change in marginal tax rates is 7,936 percentage points. If instead we assume the marginal response is
$1,000, the implicit change in marginal tax rates is 7.936 percentage points. We take the most conservative measure, assuming the income increment is the full $2,500. Thus we take this taxpayer’s kink size to be 3.17 percentage points.\footnote{The formula for kink size, given an income increment of $X \leq 2500$, is\((79.36/X) \times 100\%).}