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Essays in Public Finance and Psychology and Economics

by

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Abstract

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President Obama – in the executive order *Using Behavioral Science Insights to Better Serve the American People* – states that: "To more fully realize the benefits of behavioral insights and deliver better results at a lower cost for the American people, the Federal Government should design its policies and programs to reflect our best understanding of how people engage with, participate in, use, and respond to those policies and programs." The conventional assumption is that individuals respond rationally to incentives. Most government programs have been designed on this premise. This dissertation aims at empirically analyzing the responses of individuals to government programs in light of the findings from behavioral sciences in order to design better interventions.

One of the most important interaction individuals and firms have with the government is through the tax system. Virtually every transaction is subject to taxes, be it consumption taxes, income taxes, property taxes, etc. As such, taxes constantly affect our behavior in directions that are not always properly understood.

In the first chapter, I show that individuals forgo substantial tax benefits to avoid the hassle costs of filling out forms and collecting receipts. To do so, I use a quasi-experimental design and a novel identification strategy. Employing a sample of US income tax returns, I observe the preferences of taxpayers when choosing between itemizing deductions and claiming the standard deduction. Taxpayers forgo tax savings to avoid the hassle cost of itemizing, resulting in an average burden of itemizing of $644, with substantial heterogeneity. A revealed preference argument implies that itemizing deductions is as painful as working 19 hours. The burden of tax filing is larger for richer households, consistent with the fact that the value of time increases with income.

The second chapter explores two explanations for the large magnitude of forgone deductions. First, it could be due to an extreme aversion to filing taxes. Such aversion implies that itemizing deductions imposes aggregate hassle costs of 0.2% of GDP and back-of-the-envelope extrapolations to filing federal taxes yield an overall burden of 1.25% of GDP. Second, if taxpayers are time inconsistent they may forgo large benefits even when hassle costs are relatively small due to procrastination. I provide evidence most consistent with

taxpayers being present-biased. Both explanations – whether driven by preferences or mistakes – suggest that the burden of tax filing is significantly larger than previously estimated. I also discuss policy implications of the result in light of each explanation.

In the third chapter I document the existence of a novel dataset that can be used to study the international migration of high skilled workers. In particular, this type of datasets can inform researchers and policymakers on the extent to which taxpayers migrate to avoid taxes. I provide new series on the international migration of high skilled workers educated in France from 1944 to 2012. To do so, I use alumni databases to track the location of graduates from leading French post-secondary institutions. The proportion of high skilled individuals working in France has been steadily decreasing from 1944 to 2004. Recent years have seen an increase in the percentage of graduates staying in France in contradiction with the view that high taxes and administrative costs have been leading high skilled workers to leave France.

In Memory of Faiza Benzarti

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I am extremely grateful to my advisor Emmanuel Saez for the astounding amount of time he spent with me, the patience he has shown throughout the process and the permanent mark he left on the way I conduct research and think about Economics in general. Emmanuel's availability and wise guidance were crucial and knowing that I could rely on him at all times was essential in giving me the necessary confidence one needs when starting research. No matter how many times I got lost in my work, Emmanuel was always able to steer me back to the frontier. Emmanuel's mentorship has been key to my transformation form graduate student to scholar. And as I am starting my career as researcher, I do so with the confidence that I received the best training one can get.

I spent numerous hours in Alan's office discussing details of the tax code, and those times were very enjoyable. Alan's knowledge of the tax code and of the field of public finance in general is beyond limit and sometimes I found myself staring at the shelves and shelves of books in his office wondering if he knew every single one of them by heart. I still remember sitting in his class in my second year, listening to him telling us about fascinating quirks of the tax code and hoping one day I would know half as much. Alan also shared Emmanuel's extreme kindness and generosity with his time, so much so that I am inclined to believe that public finance scholars are particularly prone to believing in the public good more than others.

When I first got to Berkeley, I wanted to be a theorist, but it was Stefano DellaVigna's class and the passion with which he taught his class about people's biases that convinced me to pursue empirical work. Stefano was extremely supportive throughout my time at Berkeley. Some of his advice is engraved in my memory.[1] My interactions with him were always like a breath of fresh air, I knew I would always get a new viewpoint, new ideas for things to test, for exogenous variation and more whenever I would meet with him.

I got to meet Ned Augenblick at the later stages of my studies and I am very grateful for that fortuitous encounter. Ned gave me precious advice over the job market and research in general. I remember being done with flyouts and waiting anxiously for offers and meeting Ned who told me that I should embrace the uncertainty that I am experiencing because it's unlikely that I will get to live that again: that made me more serene.

I took Matthew Rabin's Psychology and Economics class in the first semester of my first year – in lieu of Micro Theory – and that left a permanent footprint on the way I think about economics. Matthew was also the first person I ever to talked to about research and he showed a lot of patience at those early stages. I always strived to emulate Matthew's attitude towards research – relentless questioning of assumptions, aiming at doing good research not necessarily research that can be well published, documenting effects even if they are small etc. – and I will continue doing so.

[1] Among others: Always cluster your standard errors. Research gets easier over time. Part of doing research is learning to deal with failed projects. And many others!

Shachar Kariv was always there to talk to me whether to discuss research or just the way things are going. Shachar was my person to go to when feeling down, he knew how to instill enthusiasm in me! He was particularly helpful at job market time, when preparing me for the interviews and for that I will always be grateful.

I am also grateful to the friends that I met at Berkeley. Emiliano Huet Vaughn is an amazing person, talking to him was always intellectually stimulating but he is also extremely kind and spent a lot of time prepping me and coaching me during the job market. Dorian is one of the best friends one could hope for but when coupled with being also the best co-author one could possibly imagine, the synergies are infinite and for these reasons I am very happy I got to meet him and Kristen. I also want to thank Eva Cheng and David Silver for countless nights of drinking beer, eating pizza and playing Mario Kart. Having dinner with Aniko Oery and Misha Shkolnikov were some of my favorite times at Berkeley. I also would like to thank Takeshi Murooka and Antonio Rosato.

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And finally, there are no words to express my gratitude to Alisa, for being my best friend and far better half, thanks to whom these past six years were some of the best of my life.

Chapter 1

How Taxing Is Tax Filing? Leaving Money on the Table Because of Hassle Costs.

1.1 Introduction

While there is a long tradition in public finance of assessing the magnitude of the efficiency cost of taxation, very little attention has been given to the burden of filing taxes. Every year, more than 140 million taxpayers have to file taxes in the US. With the tax code becoming increasingly complex, taxpayers have to spend a significant amount of time filling out the 1040 form, various schedules and keeping records of their transactions. The prevalence of hassle costs is a possible – yet unexplored – explanation for the incomplete take up of benefits such as the Earned Income Tax Credit (EITC) or Unemployment Insurance.[1] This has been emphasized by President Obama[2] who insists on the need to: "Help qualifying individuals (...) access public programs and benefits by (...) streamlining processes that may otherwise limit or delay participation – for example, removing administrative hurdles, shortening wait times, and simplifying forms"

How large is the burden of tax filing and are taxpayers forgoing benefits because of it? I answer this question by observing the choice of individuals over two tasks offering a trade-off between hassle costs and benefits. Itemizing deductions requires some effort cost but can provide large tax savings. Claiming the standard deduction saves time and effort but results in more taxes due.

With no hassle costs, taxpayers should itemize if the benefit of itemizing is greater than zero. With hassle costs, itemizing is only beneficial if it reduces the tax bill by more than the cost of itemizing. This implies that if hassle costs are non-zero, some taxpayers will claim the standard deduction even though the sum of their deductions is greater than the

[1]See for example Blank and Card (1991) for UI and Currie (2004) for other government programs.

[2]*Using Behavioral Insights to Better Serve the American People*, Executive Order, September 2015

standard deduction amount. The main identification challenge is to differentiate between individuals who fail to itemize deductions because of hassle costs from individuals who claim the standard deduction because their total deductions are smaller than the standard deduction amount. This is particularly difficult because taxpayers who claim the standard deduction are not required to report their deductions, implying that their true level of deductions is not observable in tax data.

If individuals are forgoing tax benefits because of hassle costs, there should be a missing mass in the density of deductions immediately to the right of the standard deduction threshold. I test this hypothesis by graphing the density of deductions for years ranging from 1980 to 2003 using a representative sample of US tax returns. The shape of the density function suggests the presence of a missing mass in the neighborhood of the standard deduction. To confirm that this shape is due to taxpayers responding to the standard deduction, I turn to a quasi-experimental design. Following an increase in the standard deduction amount in 1971 and 1988, I observe a drop in the mass of itemizers in the neighborhood of the post-reform standard deduction threshold. The post-reform density is systematically lower than the pre-reform one in the neighborhood of the post-reform standard deduction threshold and the two densities overlap further away from the standard deduction. I ensure that no other reforms are affecting the densities of itemized deductions.[3]

I use the missing mass to construct the distribution of forgone benefits. I find significant heterogeneity among taxpayers. Some taxpayers still itemize even when savings are modest and some forgo large tax benefits, resulting in an average burden of itemizing of $644 per person.

If individuals switch to the standard deduction because they value their time more than the benefits they can derive from itemizing, richer households should forgo more tax benefits than poorer ones. To test this hypothesis, I break down individuals by income deciles and repeat the same identification strategy outlined above. The results show an increasing relationship between forgone tax benefits and income - while controlling for the marginal tax rate - consistent with the hypothesis that tax filing imposes a higher burden on richer individuals because they have a higher marginal value of time. Using a revealed preference argument and back of the envelope calculations, I estimate that itemizing is perceived to be as painful as working 19 hours.

The existence of a missing mass in the neighborhood of the standard deduction is consistent with taxpayers forgoing benefits to avoid the cost of itemizing. I consider alternative explanations for the missing mass. The first of such explanations is that the standard deduction acts a concave kink point, effectively changing the price of a deduction. A second explanation is that some taxpayers could be evading taxes by exaggerating their deductions. If they also exaggerate the probability of being audited, they may decide to claim the standard deduction and avoid an audit. These two explanations would lead to a missing mass

[3] My estimates are not affected by the Alternative Minimum Tax, variation in marginal tax rates and the phase out of the personal interest deduction in 1987. Details are provided in section 1.6.

in the neighborhood of the standard deduction.[4] These theories predict that taxpayers will respond to variations in marginal tax rates but should not respond to variations in income. The fact that forgone benefits increase with income - while controlling for the marginal tax rate - supports the hassle costs explanation over alternatives. A second test is to consider deductions that are easy to adjust[5] and contrast them with deductions that are likely to be inert.[6] Taxpayers who are still itemizing even though they are close to the standard deduction should have an abnormally high proportion of inert deductions. This prediction is empirically rejected: the proportion of the easy and hard to adjust deductions is comparable both close to and away from the standard deduction. I also carry calibrations of each model to show that they cannot explain the magnitude of the forgone benefits.

The cost of itemizing is the sum of two separate costs: the cost of record keeping and the cost of filling out Schedule A. Which one of the two is higher and drives the result? To answer this question, I consider the outside option of using a tax preparer. Tax preparers can provide assistance with filling out forms but they cannot perform any record keeping. The fee charged by tax preparers to file Schedule A is therefore an upper bound on the cost of filling out Schedule A. The fee charged by tax preparers for filing *both* the 1040 form and Schedule A is less than $220, implying that most of the cost is driven by record keeping.

The results of this paper have implications in several dimensions. First, this is – to my best knowledge – the only paper to provide estimates of the burden of filing taxes by directly observing the behavior of taxpayers and using administrative tax data. Two other papers address this question using tax data: Pitt and Slemrod (1989) and Slemrod (1989). Because they cannot observe the preferences of taxpayers, they estimate a discrete choice model. They find smaller hassle costs.[7] There is also a literature that uses survey evidence to estimate hassle costs.[8] Although informative of the time spent filing taxes, it does not capture the preferences of taxpayers and in particular any aversion to filing taxes or any behavioral biases. It also suffers from the usual biases of surveys including high attrition rates and measurement errors.[9] The revealed preference estimates of the cost of itemizing derived in this paper are significantly larger than those estimated using surveys but are consistent with the amount of benefits forgone by individuals in other settings.[10] These results further emphasize the policy relevance of reducing hassle costs and advocates for a simplification of the tax code.

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[4] A concave kink point would also create a missing mass to the left of the standard deduction, effectively leading to a bi-modal distribution.

[5] The literature has documented extensive responses of charitable donations to tax incentives.

[6] The mortgage interest deduction is one such example because mortgages are usually signed for long periods of time. The state tax deduction is another one as it relies on income which has been found to be not very responsive.

[7] Possibly because of the structural assumptions they have to make. Section A.1 discusses how our two approaches relate and some of the pitfalls of using a discrete choice model to estimate the hassle cost of itemizing deductions.

[8] The hassle costs estimated by this literature are listed in table A.5

[9] Slemrod and Sorum (1985) and Slemrod (1989) for example report an attrition rate of 71.3%

[10] See table A.6 listing research documenting the magnitude of forgone benefits in other settings.

There is an extensive literature that documents low take up rates of government provided benefits.[11] Three explanations are generally offered: lack of information about the program, stigma costs and hassle costs. This paper is the first to disentangle hassle costs from lack of information and stigma costs and to show that they have a significant effect on benefit take up. The literature has mostly focused on the role of information. Bhargava and Manoli (2011) for example show that failure to claim the EITC can be explained by lack of information about the program but do not address hassle costs. My findings also provide a plausible and additional explanation for other phenomena reported by the literature. Jones (2012) shows that taxpayers fail to adjust their tax withholding resulting in forgone interest payments. He explains his results with inertia. An additional explanation could be the cost of filling out form W4 and sending it to the IRS. Engström et al. (2013) and Rees-Jones (2013)[12] show that taxpayers who have a balance due are more likely to reduce their balance to zero by claiming additional deductions. They provide compelling evidence that this behavior is driven by loss aversion. My estimates show that the cost of sending a cheque to tax authorities could be an additional channel for their result.

This paper is also related to a literature in marketing[13] and behavioral economics[14] documenting instances in which consumers fail to claim rebates. Some estimates suggest that only 1% of coupons are eventually redeemed.[15] Explanations of this findings are scarce. My results show that transaction costs (mailing the coupon etc.) are a plausible channel for this phenomenon.

Finally, this paper adds to a long tradition in public economics emphasizing the need to screen out applicants for welfare benefits by imposing high hassle costs[16] such as waiting in line, filling out forms etc. Poorer individuals value their time less – possibly because they are unemployed – and such policies can successfully target them by screening out richer individuals. My results show that this effect is indeed true because richer individuals tend to forgo more benefits than poorer ones. However, given how large the costs are, such policies could be screening out too many individuals. In addition, time inconsistency could lead to unwanted distortions such as screening out naive individuals versus rational ones rather than rich ones versus poor ones.

1.2 Data and Institutional Background

The Decision to Itemize Deductions

Taxpayers can reduce their taxable income by claiming deductions. Consider, for example, a single person with an income of $150,000. In 1989 her marginal tax rate is 28%. If the

[11] See Currie (2004) for a survey of the literature.
[12] See also Feenberg and Skinner (1989).
[13] Silk and Janiszewski (2008).
[14] Ericson (2011) and Letzler and Tasoff (2014).
[15] Inmar (2012).
[16] Nichols et al. (1971) and Duclos (1995).

person spends a total of $10,000 on different expenses that she is allowed to deduct from her income, her tax liability is reduced by $2,800. If instead she decides to claim the standard deduction – which in 1989 was $3,100 – her tax liability is reduced only by $868.

The decision to itemize deductions only entails comparing two numbers: the sum of itemized deductions to the standard deduction amount. Itemizing however is administratively burdensome as it requires collecting several documents and working through a separate tax form.

A rational taxpayer should account for these costs: if her total itemized deduction exceeds the standard deduction by an amount smaller than the cost of itemizing, she should claim the standard deduction even if it results in a larger tax liability.

Approximately two thirds of the population claim the standard deduction. The standard deduction amount varies by filing status (single, joint, married fling separately and head of household) and by whether the person is blind or older than 65.

The Cost of Itemizing

Itemizing deductions is a two-step process. First, the taxpayer has to keep a record of all the expenses she wants to deduct during the year she is filing taxes for, year t. Second, she has to file a separate form when itemizing: Schedule A.

The majority of taxpayers itemize four types of deductions:

- State and local income taxes: these are taxes paid in year t to the state or to the locality. They are reported on form W2 received in January of year $t+1$. On average they represent 17% of total deductions.
- Mortgage interest: this is the interest paid to finance the main or second home of the taxpayer. It is reported on form 1098[17] which is received in January of year $t+1$. On average they represent 40% of total deductions.
- Real estate taxes: these are taxes paid on real estate owned by the taxpayer. They can be found on the 1098 form, in financial records or by calling the county tax assessor. On average they represent 14% of total deductions.
- Charitable donations: any payment made for charitable purposes including to religious institutions. These payments are not subject to third-party reporting. The taxpayer has to keep records of her own receipts. On average they represent 12% of total deductions.

In addition, some taxpayers can also deduct other taxes (sales taxes in some years), other interest expenses (credit-card interest in some years), casualty or theft losses, medical and dental expenses and miscellaneous deductions.

[17] Mortgage interest on the purchase of a Recreational Vehicle (RV) or a boat used as a primary or secondary residence is not reported on the 1098. This is unlikely to bias my results given that few people live in RVs or boats.

Schedule A is relatively easy to fill out especially if the taxpayer only needs to itemize the most common deductions outlined above. All she has to do is copy numbers from form 1098, form W2 or charitable contribution receipts, sum them up and copy the sum in the 1040 form. There are no complicated tax schedules nor intricate tax operations. Record keeping is more time consuming as one has to archive the various evidence of expenses to be able to recover them when the tax season arrives. It is however easier to keep track of deductions that are third-party reported given that taxpayers receive the W2 and 1098 in January of year $t + 1$.

Data

The dataset used to carry this analysis consists of annual cross sections of individual tax returns. It is constructed by the IRS and called the Individual Public Use Tax Files. They are commonly referred to as the Statistics of Income (SOI) files. The data is available annually for the periods that I am analyzing. The number of observation per year ranges from 80,000 to 200,000. The repeated cross sections are stratified random samples where the randomization occurs over the Social Security Number. The data over samples high-income taxpayers as well as taxpayers with business income but weights are provided by the IRS allowing my analysis to reflect population averages.

In addition, I use a panel of tax returns known as the University of Michigan tax panel. The panel covers 1979 to 1990 and contains the same variables as the SOI files but has a smaller sample size (less than 40,000 observations per year).

In rare cases individuals are forced to itemize deductions even though the standard deduction amount is larger than their deductions (details in section A.3). I drop these individuals from the sample.

Sample restrictions are detailed in appendix section A.2.

1.3 Results

In this section I reconstruct the counterfactual density of itemizers and estimate the burden of itemizing deductions. First, if taxpayers are claiming the standard deduction even though they could profit from itemizing, there should be a missing mass in the neighborhood of the standard deduction. This missing mass is observed for any year (figure 1.1) and any filing status. Second, to show the causal relationship between the standard deduction and the missing mass in the neighborhood of the standard deduction, I use two reforms that increase the standard deduction amount, in 1971 and 1989 (see table A.1). I observe that the missing mass follows precisely the standard deduction threshold (figures 1.2a and 1.2b). Third, I develop a method to recover the counterfactual density of deductions. Finally, I use this counterfactual density to estimate the distribution of the burden of itemizing deductions in the population.

Missing Mass In the Neighborhood of the Standard Deduction

If some taxpayers are claiming the standard deduction even though the sum of their itemized deductions is greater than the standard deduction there should be a missing mass in the neighborhood of the standard deduction threshold.

I graph the density of deductions for all years ranging from 1980 to 2006 by bin sizes of $2,000[18] in figure 1.1. The bin closest to the standard deduction only includes itemizers whose deductions are strictly larger than the standard deduction amount. Notice that the density is systematically low in the neighborhood of the standard deduction and then increases and peaks 2 to 3 bins away. This is consistent across years and across filing status.

The shape of the density of itemizers in the neighborhood of the standard deduction suggests that the density is discontinuous at the standard deduction. However, I cannot observe the density of itemizers below the standard deduction threshold because taxpayers who claim the standard deduction are not required to list their true deductions. In figure 1.3, I consider the three different scenarios for the counterfactual density of deductions of taxpayers who claim the standard deduction. Approximately two-thirds of taxpayers claim the standard deduction which means that the density below the standard deduction threshold cannot be increasing from zero onwards and then connect with the density on the right-hand side of the standard deduction (graph (a)), as this would fail to account for a large portion of the population. If the density is smoothly decreasing on the left-hand side of the standard deduction threshold and it is single-peaked, then it is likely that the density is discontinuous at the standard deduction threshold (graph (c)). But I cannot rule out double peaked distributions (graph (b)) when only using one cross section and without knowing what the true distribution of total deductions is below the standard deduction threshold. This is why I turn to a quasi-experimental approach.

Identifying the Missing Distribution

I exploit large increases in the standard deduction amounts to analyze the effect of the standard deduction on itemizers. The largest of these changes happened in 1971 and 1988. Table A.1 reports that the standard deduction increased respectively by 50% and 33%.

I compare the pre-reform year to the post-reform year to account for lagged behavioral responses. Figures 1.2a and 1.2b graph the density of deductions in pre and post-reform years for the 1971[19] and 1988 reforms. Notice that the shape of the distribution in year t+1 mirrors that of year t-1 and that the missing mass precisely follows the new standard deduction threshold. This shows that some itemizers switch to the standard deduction once it is increased even though their deductions are larger than the standard deduction.

[18] all dollar amounts are in 2014 dollars in the rest of the paper.

[19] For the 1971 reform, I compare the pre-reform year to the reform year because another reform of the standard deduction takes place in 1972. This means that the 1971 estimate is likely to be a lower bound as it does not account for any lagged response in 1972.

The fact that the missing mass closely follows the standard deduction establishes that there is a discontinuity at the standard deduction due to the effort cost of itemizing. If this missing mass was a feature of the distribution and not due to the standard deduction, it should not follow the standard deduction once it is increased.

1.4 Economic Interpretation of the Missing Mass

The interpretation of the missing mass in the neighborhood of the standard deduction relies on the simple intuition that taxpayers bear a cost when itemizing but no cost when claiming the standard deduction. I outline this explanation in this section, show that it is consistent with the empirical patterns of the distribution and contrast it - in section 1.6 - with other explanations by empirically testing predictions of each model.

Hassle Cost

Denote by $f(.)$ the probability density function (PDF) of itemizers when facing no cost and $g(.)$ the PDF of itemizers when there is a cost to itemizing. $C(.)$ the cumulative distribution function in the population defined over $[0, c_{max}]$, where c_{max} denotes the largest cost an individual can have, and $c(.)$ denotes the corresponding PDF. For every x, $C(x)$ is equal to the proportion of the population with a cost smaller than x and $c(x)$ is equal to the proportion of the population with cost equal to x.

Denote by d the distance to the standard deduction, which is also equal to the benefit of itemizing. At a given point d, the mass of itemizers $g(d)$ is equal to the true (undistorted) mass of itemizers $f(.)$ minus the proportion of individuals with a cost greater or equal to d i.e $g(d) = f(d) - (1 - C(d))$.

Denote by the T after tax-benefit of itemizing deductions and by S the benefit of claiming the standard deduction. Notice that $T - S = d$.

If cost $c()$ is constant in the population with $c(x) = c$ for any x in $[0, c_{max}]$, then any taxpayer who could derive $T - S < c$ from itemizing will claim the standard deduction because the cost of itemizing exceeds its net benefit. The observed distribution of itemizers will therefore be equal to:

$$g(d) = \begin{cases} 0, & \text{if } d < c_{max} \\ f(d), & \text{if } d \geq c_{max} \end{cases}$$

As such, we would observe a missing mass for any taxpayer such that $T - S < c_{max}$ with nobody itemizing in the $[0, c_{max}]$ region.

If the cost is heterogenous, then

$$g(d) = \begin{cases} f(d) - (1 - C(d)), & \text{if } d < c_{max} \\ f(d), & \text{if } d \geq c_{max} \end{cases}$$

where $f(.)$ is decreasing in the neighborhood of the standard deduction[20]. $C(.)$ is - by definition of a CDF - increasing in d, which implies that $f(d) - (1 - C(d))$ is increasing in d. This implies that $g'(d) > 0$ if $d < c_{max}$ and $g'(d) < 0$ otherwise. In other words - with heterogenous costs - g(.) should be inversely U-shaped and peaks at $d = c_{max}$.

This is consistent with the patterns observed in figures 1.1, 1.2a and 1.2b.

Recovering the Counterfactual Distribution Using the Reform Years

To calculate the distribution of forgone benefits in the population, I need to reconstruct the counterfactual distribution of itemizers.[21] This section explains this process.[22]

Identification Assumptions

I need to make two assumptions to reconstruct the counterfactual:

- **A1**: The cost is constant across years.
- **A2**: The cost does not increase with the level of deductions.

Assumption A1 can be verified by graphing two densities in years with no reforms and ensuring that they are overlapping. This is confirmed in figure A.7.

Assumption A2 is not testable but it makes intuitive sense: the cost of itemizing \$10,000 of mortgage interest should be as costly as itemizing \$100,000. This assumption is made by Pitt and Slemrod (1989) as well.

Counterfactual Distribution

I generate bins of a given size n. Denote by i the distance of a given bin to the standard deduction and by t the year I am considering. b_i^t is the number of taxpayers who have total deductions in the range $[(i-1) \times n + S, i \times n + S]$ where S denotes the standard deduction amount in year t.

For example, if $S = \$10,000$ and $n = \$2,000$ then b_5^{1987} counts the number of itemizers who are located 5 bins away from the standard deduction in 1987, i.e. their total deductions fall in the range $[\$18,000, \$20,000]$.

[20]This is due to the fact that approximately 65% of the population claims the standard deduction. Unless $f(.)$ is bi-modal (which I address and reject in section 1.6, the distribution has to be decreasing as illustrated in figure 1.3.

[21]I cannot use the pre-reform year as a counterfactual as it might also be distorted by its proximity to the standard deduction.

[22]Additional explanations - including examples and graphical illustrations - are provided in appendix section 1.4.

Denote by $m \geq 1$ the number of bins by which the standard deduction increases after the reform. If the standard deduction increases by $4,000, and the bin size $n = \$2,000$, then $m = 2$.

Recall that $C(.)$ denotes the Cumulative Distribution Function of the cost of itemizing with support $[0, c_{max}]$.

Define $c_i = \frac{C(i+n)-C(i)}{1-\tau}$, where τ is the marginal tax rate.[23] c_i denotes the proportion of individuals who have a cost of itemizing in the range $[i, i+n]$.

If $m < c_{max}$ i.e. the increase in the standard deduction created by the reform is smaller than the range of the cost, I cannot use the density in year t as a counter-factual for year $t+2$ as the year t density is likely to be distorted and will yield an underestimate of the cost. For this reason, I need to reconstruct the counterfactual density.

Denote by $\widetilde{b}_i^t$ the counterfactual density of itemizers in bin i and in year t.

Assuming nothing else but the cost of itemizing affects the densities between the pre and post reform years, the true counterfactual densities pre and post reform should overlap, implying:

$$\widetilde{b}_{i+m}^t = \widetilde{b}_i^{t+2}. \tag{1.1}$$

By definition and for any i and t

$$c_i = \widetilde{b}_i^t - b_i^t. \tag{1.2}$$

Equations 1.1 and 1.2 imply:

$$c_i = \widetilde{b}_{i+m}^t - b_i^{t+2}. \tag{1.3}$$

Denote by J the smallest j such that $c_j = 0$. J is the bin at which no taxpayer is willing to forgo deductions anymore. If the cost of itemizing is finite, J should exist and be unique. In addition, for any $j \geq J$, $c_j = 0$.

$c_J = 0$ and equation 1.3 imply:

$$\widetilde{b}_{J+m}^t = b_J^{t+2} \tag{1.4}$$

We know from equation 1.2 and $c_j = 0$ for any $j > J$ that:

$$\widetilde{b}_{J+m}^t = b_{J+m}^t \tag{1.5}$$

Equations 1.4 and 1.5 therefore imply that:

$$b_{J+m}^t = b_J^{t+2} \tag{1.6}$$

Equation 1.6 holds true - by induction - for any $j \geq J$. It states that J can be identified empirically: it is the bin at which the pre and post reform densities overlap and keep overlapping.

[23]It is divided by $1-\tau$ so that the cost of itemizing is in pre-tax dollars as for deductions.

From equation 1.2 and the fact that for any $j \geq J$ $c_j = 0$, it follows that for any $j \geq J$ $\widetilde{b}_j^t = b_j^t$. In particular:

$$\widetilde{b}_{J+m-1}^t = b_{J+m-1}^t$$

Equation 1.3 for $i = J - 1$ is:

$$c_{J-1} = \widetilde{b}_{J+m-1}^t - b_{J-1}^{t+2} = b_{J+m-1}^t - b_{J-1}^{t+2} \tag{1.7}$$

Equation 1.7 states that to calculate c_{J-1} one only needs to take the difference between the *observed* pre and post-reform densities. This holds true because $c_{J+m-1} = 0$ implying that b_{J+m-1} is the true counterfactual for b_{J-1}^{t+2}.

By induction, it follows that as long as $j + m \geq J$:

$$c_j = \widetilde{b}_{j+m}^t - b_j^{t+2} = b_{j+m}^t - b_j^{t+2} \tag{1.8}$$

Equation 1.8 provides an expression for $c(j)$ as long as $c(j + m) = 0$.

For any j such that $c_{j+m} > 0$, equation 1.8 is replaced by:

$$c_j = \widetilde{b}_{j+m}^t - b_j^{t+2} = b_{j+m}^t + c_{j+m} - b_j^{t+2} \tag{1.9}$$

Equation 1.9 has an additional term c_{j+m}, which corrects b_{j+m}^t to account for the fact that it is distorted by its proximity to the standard deduction.

Equation 1.9 defines c_j as a function of c_{j+m} and the empirically observed densities b_{j+m}^t and b_j^{t+2}. c_{j+m} was previously calculated using equation 1.8. Using (backwards) induction, I can therefore derive each of the $c_J, c_{J-1}, c_{J-2}, ..., c_0$.

This is the process I follow to reconstruct the counterfactual density of itemizers used to calculate the average forgone benefit in the following section. This reconstructed counterfactual is graphed in figure 1.5 for the 1989 distribution. An extrapolation of the density below the standard deduction accounts for the 65% of the individuals claiming the standard deduction.

To calculate the standard errors of the difference between the bins in the 1987 and 1989 densities and 1970 and 1971 densities, I use a bootstrap procedure with 100 replications. The results are reported in table A.2 and table A.3. The difference between the first and second bins is statistically significant with large z statistics (6.55 and 3.47). The rest of the bins are all overlapping with differences that are not significant even at the 10% level, at the exception of bin 10, 11 and 13 that are statistically significantly different at the 5 and 10% level, with differences of very small magnitude (less than 10 times that of the first or second bins).

Counterfactual Distribution Reconstruction Using an Illustrative Example

To calculate the burden of itemizing deductions I create bins of \$2000.[24] I calculate the weighted frequency of individuals located in those bins. I subtract the mass of the 1989 bin

[24] I also consider \$1,000 bin sizes in table 1.2, which yields similar results.

from the mass of the corresponding bin in 1987 after adjusting the amounts to account for inflation.

To calculate the standard errors of the difference between the bins in the 1987 and 1989 densities and 1970 and 1971 densities, I use a bootstrap procedure with 100 replications. The results are reported in table A.2 and table A.3. The difference between the first and second bins is statistically significant with large z statistics (6.55 and 3.47). The rest of the bins are all overlapping with differences that are not significant even at the 10% level, at the exception of bin 10, 11 and 13 that are statistically significantly different at the 5 and 10% level, with differences of very small magnitude (less than 10 times that of the first or second bins).

This approach allows me to measure the percentage of individuals that claim the standard deduction even though their total itemized deductions exceed the standard deduction amount by multiples of $2,000.

Once I get those percentages, I need to adjust the 1987 distribution to get the true counterfactual as it might be distorted by its proximity to the standard deduction threshold. For clarity I associate each bin with a number that denotes its distance from the standard deduction amount. For example, in 1987 the standard deduction amount is $7,865. This means that bin [7865, 9865] is called bin number 1 in 1987 and bin [9865, 11865] is called bin number 2 in 1987. Bins in 1989 are defined in a similar way relative to the standard deduction amount of $9,991: bin [9991, 11991] is bin number 1 and bin [11991, 13991] is bin number number 2.

To recover the counterfactual distribution of deductions I use the fact that the distribution of costs should be the same in 1987 and 1989.[25] I consider the first bins for which the 1987 and 1989 densities are overlapping. Figure 1.2a shows that these are bin number 3 in 1989 and bin 4 in 1987. In 1989, taxpayers located in bin number 3 can save from $4,000 to $6,000 worth of deductions. Given that the 1987 and 1989 densities are overlapping in the 1989 bin 3, no taxpayer is willing to forgo more than $4,000 worth of deductions. In 1987, taxpayers who can save from $4,000 to $6,000 of deductions are located in bin 3. Since I assume that the cost is the same across years, this means that 1987 is the undistorted counterfactual for the 1989 density in bin 2. Bin 1 of the 1989 density is compared to bin 2 of the 1987 density. However, from observing the difference between the 1987 bin 3 and 1989 bin 2, I know that some taxpayers will forgo deductions, biasing the 1987 bin 2 downward. By using the difference between the 1987 bin 3 and 1989 bin 2, I can calculate this bias and correct bin 2 in 1987 to get the true counterfactual for the 1989 bin 1.

The following hypothetical example illustrates the adjustment process and formalizes the approach I use to recover the true counterfactual density. I generate an undistorted hypothetical density of deductions in figure 1.6. Each bin size is equal to $100. I assume that the distribution of the burden of itemizing in the population is given by the following:

- 40% have a burden lower than $100

[25] It is reasonable to assume that the time required to itemize deductions in 1987 and 1989 is the same because there were no changes to the Schedule A form or to the record keeping requirements.

- 70% have a burden lower than \$200
- 85% have a burden lower than \$300
- 95% have a burden lower than \$400

I introduce a standard deduction in the second bin in figure 1.6 and apply the distribution assumed above to the density. To calculate the distribution of the burden in this scenario, I would simply compare the percentage difference between the true density and the distorted one. However, the true density is unobserved. In order to reconstruct it, I use an exogenous increase in the standard deduction. Figure 1.6 assumes that the distribution of the burden is the same across years and introduces a reform that increases the standard deduction amount by \$200 (2 bins). I denote by d_i the distortion introduced by the standard deduction in bin i. 40% of the population experiences a burden smaller than \$100. This means that $1 - 40\% = 60\%$ will claim the standard deduction in the first bin. This implies that the first bin is distorted by 60% i.e. $d_1 = 60\%$. Similarly, $d_2 = 30\%$, $d_3 = 15\%$ and $d_4 = 5\%$ and $d_i = 0$ for any $i > 4$.

Denote by b_i^t the bin density, where i is the distance (in bins) to the standard deduction and t is the year. Year t corresponds to the pre-reform year and year $t+1$ to the post-reform year. When overlapping the density of deductions for year t and year $t+1$, b_i^t will be at the same location as b_{i-2}^{t+1} because the standard deduction increases by 2 bins because of the reform. If $b_i^t - b_{i-2}^{t+1} = 0$ then $d_{i-2} = 0$. I then start with the first undistorted bin. In graph 1.6 it corresponds to bin 7 in year t:

- $b_7^t - b_5^{t+1} = 0$ implies that $d_5 = 0$. This means that for both year t and $t+1$, b_5, b_6, b_7 etc. are undistorted as $d_5 = 0$ means that nobody has a burden greater than 500. This also means that I can use b_6^t as the true counterfactual to calculate d_4.
- $b_6^t - b_4^{t+1} = 5\%$ implies that $d_4 = 5\%$. Given that b_6^t is the true density (from the previous bullet point), I can use $\frac{b_4^t}{1-d_4}$ as the *true* counterfactual to calculate d_2.
- $b_5^t - b_3^{t+1} = 15\%$ implies that $d_3 = 15\%$. Given that b_5^t is the true density (from the first bullet point), I can use $\frac{b_3^t}{1-d_3}$ as the *true* counterfactual to calculate d_1.
- To calculate d_2 I need to use b_4^t. But I know from above (second bullet point) that b_4^t is distorted. This implies that the counterfactual density that I need to use to calculate d_2 is $\frac{b_4^t}{1-d_4}$ rather than b_4^t. Hence, $d_2 = \frac{b_4^t}{1-d_4} - b_2^{t+1} = 30\%$.
- Similarly, to calculate d_1 I need to use b_3^t. But I know from the third bullet point that b_3^t is distorted. This implies that the counterfactual density that I need to use to calculate d_3 is $\frac{b_3^t}{1-d_3}$ rather than b_3^t. Hence, $d_1 = \frac{b_3^t}{1-d_3} - b_1^{t+1} = 60\%$.

The distribution of the burden d_i derived using this method allows me to precisely recover the distribution of the burden that I assumed above. This example shows that I am able to recover the true (unobserved) density by using the pre-reform and post-reform densities. The cost distribution d_1, d_2 etc. allows me to calculate the distribution of the burden and recover the true density of deductions in figure 1.5.

Estimation of the Burden of Itemizing Deductions

Distribution of the Burden

The counterfactual density that I constructed using the method outlined in the previous section allows me to observe the number of taxpayers who itemize in every bin and contrast it with the number of taxpayers who should have been itemizing had there been no cost to itemizing.

Following notations from the previous sections, denote by d the amount of tax savings a given taxpayer i can derive from itemizing and c_i the burden of itemizing. d is a random variable: it depends on the mortgage interest, state and local taxes etc. of individual i and the level of the standard deduction, c_i on the other hand is inherent to each taxpayer. What I am able to observe is whether taxpayer i itemizes for a given level of savings d. For a given realization of d a taxpayer who itemizes has a burden $c_i < d$. Denote by d_k the amount of savings a taxpayer derives from itemizing when located in bin k. I can observe the proportion p_k of the population who itemizes when assigned savings d_k: $p_k = \Pr(c_k \leq d_k) = 1 - F(d_k)$, where $F(.)$ is the cumulative distribution function (CDF) of the burden. Hence,

$$F(c_k) = 1 - p_k. \tag{1.10}$$

In bin 1 for example we know that $d_1 \in (0, 2000]$. By using the difference between the mass of itemizers and the missing mass, I observe that $p_1 = 53\%$. This implies that $F(2000) = 1 - 0.53 = 47\%$ i.e. 47% of the population has a burden that is lower than \$2000 and greater than \$0.[26]

By repeating the same procedure for the remaining bins, I can construct the CDF of c_i. I need the probability density function (PDF) to calculate the average perceived burden of itemizing, which can be derived from the CDF by taking the difference of the proportion of itemizers between each subsequent bin. Denote by m_k the PDF in bin k, then:

$$m_k = p_k - p_{k-1}. \tag{1.11}$$

The PDF and CDF are shown in table 1.1. Table 1.2 reports the CDF and PDF for a smaller bin size (\$1,000).[27]

[26] Unless some individuals enjoy filing taxes, it is safe to assume that $c_i > 0$ for any i i.e. $p_0 = 0$.

[27] Using a smaller bin size yields similar results because as the bin size is reduced, the proportion of taxpayers in a given bin changes: there are less taxpayers who itemize in the first bin when considering a bin size of \$1,000 for example.

Hassle Cost Calculation Using the 1988 Reform

Besides the standard deduction reform, the only reform happening in 1988 that could affect the amount of deductions is the personal interest deduction phase-out, which I control for (details in section 1.6). There were no other reforms affecting deductions in 1988 or 1989 and the reforms affecting the 1987 distribution do not have lagged effects (see section 1.6 for the full list of reforms and appendix section A.4 for the TRA'86 reforms). I restrict my sample to taxpayers with the same marginal tax rate (28%) and who are not subject to the Alternative Minimum Tax (AMT). There is a marginal tax rate decrease for married filing jointly with income above $45,000 (in 1987 dollars) in 1988. I control for this change by only considering taxpayers with income below $45,000.

Table 1.1 implies that taxpayers forgo large amounts of deductions, resulting in a burden of itemizing of $644 (s.e. 54.1). The average net annual wage for households in the neighborhood of the standard deduction is equal to $92,743. I assume that these households work on average 40 hours a week and 50 weeks a year. Given that all these households fall in the 28% marginal tax bracket, this results in a net wage of $33 for the household. A revealed preference argument implies that taxpayers perceive the task of itemizing to be equivalent to 19 hours of work on average. This is a lower bound as I am assuming that there is only one earner in the household and that their hourly wage is equal to the $33. If there are two earners and they work the same amount of hours, their individual wage would be $16.5. Filing the tax return only requires one person, implying that if there are two earners, they would perceive the task of itemizing to be as costly as working 37 hours.

Every year, the IRS provides cost estimates for each tax form including both the time required to fill out the form and for record keeping. In 1989, the IRS estimates that the average taxpayer needs 1 hour and 1 minute to fill out Schedule A, 2 hours and 47 minutes for record keeping, 26 minutes to learn about the form and 20 minutes to copy and assemble the documents before sending them to the IRS. This totals 4 hours and 34 minutes.[28]

Hassle Cost Estimate Using the 1971 Reform

To calculate the average burden of itemizing deductions using the 1971 reform I need to control for the change in the parallel system of standard deduction which increases from 10% to 13% of AGI. The details of the adjustment are in section 1.6. In addition, and contrary to the 1988 reform, I can only calculate the average burden of itemizing using the average marginal tax rate because there were 25 marginal tax brackets in 1970 and 1971. I also focus on married taxpayers filing jointly to simplify the average marginal tax rate calculations and use bins of $3,065 ($500 in 1970 dollars) to reduce the noise. I estimate that the average burden of itemizing deductions is $996 (s.e. 126).

[28] Guyton et al. (2003) describe the methods used by the IRS to calculate the cost of filing taxes based on surveys of taxpayers and the Individual Taxpayer Burden Model used by the IRS.

1.5 Anatomy of the Missing Mass

The Burden of Itemizing Deductions Increases With Income

If rich taxpayers value their time more than poor ones because their hourly wage is higher, we should expect them to forgo more benefits. I can verify this assertion using the income reported on tax returns.

I break down the sample by deciles of income. Because this would significantly reduce the sample size, I consider a moving average of each income decile. For example, the lower income group consists of every individual with income below the second decile threshold. And the second group consists of taxpayers with a income above the first decile and below the third decile etc. Some individuals will simultaneously belong to two groups: for example individuals whose income falls in the second income decile will belong to both the first group (income below the second income threshold) and the second group (income greater than the first decile threshold but smaller than the third decile threshold). This overlap is not a concern because the goal of this breakdown is to graph the relationship between income and forgone benefits. The precise location of a point in the income/forgone benefit space is of no particular interest. Instead, I am interested in plotting the general trend of the relationship.

Once the groups are constructed and because I have less data points, I fit a polynomial of degree 3 through each deduction bin. I construct confidence intervals around each bin. Any bins for which the confidence intervals overlap are considered as overlapping bins. Using the predicted bins from this polynomial, I am able to calculate the forgone benefits for each group by repeating the procedure developed in the previous section: I compare the distribution in 1987 to that in 1989, reconstruct the counterfactual distribution of itemized deductions and calculate the distribution of the burden of itemizing by comparing the counterfactual distribution to the true one. I only report results for the first six groups because deductions and income are positively correlated implying that there are very few high income individuals close to the standard deduction threshold. In figure 1.7(a), the x-axis represents the average income and the y-axis the average burden of itemizing for each income group. Variation in marginal tax rates across the different income groups is relatively small because there were only two marginal tax brackets in 1989[29] and most taxpayers fall in the 28% marginal tax bracket. But to be sure, figure 1.7(a) controls for variation in marginal tax rates across the different income groups. The relationship is increasing: as income increases taxpayers forgo more benefits consistent with the idea that they value their time relatively more.

Notice that even though itemized deductions increase with income, this is not what drives the increasing relationship between income and forgone benefits. Because I am using a quasi-experimental design, and comparing the same income groups before and after the reform, I am implicitly controlling for the relationship between income and deductions.

Figure 1.7(b) shows the relationship between income and the perceived hours required to itemize deductions. I assume that taxpayers work on average forty hours a day and fifty weeks a year and I divide their wages by the number of hours worked per year. By

[29]And a 33% tax rate “bubble”.

dividing the estimated burden of tax filing by this measure of their hourly wage, I get the perceived hours required to itemize deductions. The relationship between hours and income is increasing but considerably less steep than the relationship between forgone benefits and income, consistent with a value of time interpretation. It is true that rich individuals have higher dollar amounts of deductions but it is unlikely that it takes more time to itemize them. The burden of itemizing is mostly fixed and does not generally increase in the amount of a given deduction. If a taxpayer has $10,000 worth of mortgage interest, she will spend the same amount of time itemizing them as a taxpayer who has $100,000 since they only have to keep track of one form and enter one number on Schedule A.

The Response to the Standard Deduction Increase is Lagged

When comparing figure 1.4 to figure 1.2a we see that taxpayers are slow to adjust to the increase in the standard deduction – consistent with the hassle costs explanation. This suggests that taxpayers are inattentive to announcements of tax changes but learn about them while filing their taxes.

Tax Preparers and Electronic Filing

Electronic filing and the use of tax preparers may reduce the cost of filling out forms as one need not sum deductions but only enter them. However, it does not affect the cost of record keeping. Therefore, it is worth emphasizing that it *should not* fill the missing mass of itemizers close to the standard deduction because the cost of itemizing mainly stems from record keeping rather than filling out schedule A. That record keeping is the driver of the cost of itemizing is shown in section 1.6 and has been consistently documented by survey estimates of the hassle cost.[30]

To test for whether electronic filing or using a tax preparer eliminates the burden of itemizing, I graph the density of itemizers who use a tax preparer and those who use electronic filing in graph 1.8 and look for whether there is still a missing mass close to the standard deduction threshold. The missing mass is still present implying that tax preparers or electronic filing does not eliminate the burden of itemizing.

Figure 1.8(b) compares the density of taxpayers who use electronic filing to those who do not. It shows a smaller missing mass for taxpayers who file electronically than those who do not. This is consistent with the missing mass being driven by taxpayers claiming the standard deduction to avoid the cost of itemizing. However, electronic filing only slightly reduces the cost of itemizing and does not eliminate the missing mass, consistent with record-keeping being the main driver of hassle costs.

Unfortunately, I cannot perform a similar analysis for taxpayers who use tax preparers as the two densities do not overlap away from the standard deduction making a comparison

[30] See for example Guyton et al. (2003), Slemrod and Sorum (1985), Slemrod and Bakija (2008) and Blumenthal and Slemrod (1992a).

of the missing mass impossible. Figure 1.8(a) shows however that the use of tax preparers does not eliminate the cost of itemizing.

1.6 Alternative Explanations

Lack of Information

Information or cognitive abilities are unlikely to play a role in this case. I focus on taxpayers who switch from itemizing to claiming the standard deduction, therefore they should be well aware of the decision to itemize and have the cognitive abilities to do so. In addition, taxpayers are reminded on the 1040 form of the fact that they can itemize deductions as they have to make an active decision between itemizing and claiming the standard deduction.

Evasion

Could it be that taxpayers believe that itemizers are more likely to be audited than individuals claiming the standard deduction? The probabilities of audit for this portion of the population are lower than 1%[31] and are virtually the same for itemizers in the neighborhood of the standard deduction and individuals who claim the standard deduction. Assume a the taxpayer with Von Neumann-Morgenstern (VnM) preferences and a Constant Relative Risk Aversion (CRRA) utility function $U(x) = \frac{1}{1-\theta}x^{1-\theta}$. Denote by p the probability of audit, S the after tax benefit of the standard deduction, T the after tax benefit of itemized deductions, and k the cost imposed by an audit on the taxpayer, which includes both a fixed cost of being audited (collecting receipts and dealing with the IRS) and the penalty that the taxpayer may have to pay. Consider the extreme case in which all charitable deductions are false.[32] Denote by C, the proportion of charitable donations to total deductions. From figure 1.9, charitable deductions are on average equal to 13% of total deductions. Taxpayers evade taxes by reporting $C \times T$ fake deductions. Therefore, if a taxpayer is audited, her deduction level will be brought back to $T(1-C)$ from T and she will incur a cost k of being audited.

The taxpayer will itemize deductions if the expected benefit of itemizing given a probability p of facing an audit is greater than the benefit of claiming the standard deduction:

$$p\left[\frac{1}{1-\theta}(T(1-0.13)-k)^{1-\theta}\right]+(1-p)\left[\frac{1}{1-\theta}(T)^{1-\theta}\right] \geq \frac{1}{1-\theta}S^{1-\theta}. \qquad (1.12)$$

In addition, the taxpayer will switch to the standard deduction if her total deductions reduced by the amount of charitable deductions is smaller than the standard deductions i.e. $(1-C) \times T < S$. Otherwise - if she is afraid of being audited - she can still itemize and only

[31] See Miller et al. (2012) and Slemrod and Gillitzer (2013).

[32] It is very hard for taxpayers to evade the other major deductions as the mortgage interest, state tax and property tax deductions are third party reported.

claim her true deductions, she should still be above the standard deduction threshold. This implies that any taxpayer with total deductions $T > \frac{S}{C}$ would not switch to the standard deduction. This bounds the range in which there can be a behavioral response to $T \in [S, S/(1-C)]$. For $S = 10,000$ and $C = 0.13$ as shown in figure 1.9, this implies that any taxpayer with deductions exceeding the standard deduction by $1,1494 would not respond to the fear of audit. In other words, even if a taxpayer perceives the audit probabilities to be 100% they will not switch to the standard deduction because they can at most reduce their deductions by 13% which would still put them above the standard deduction. Therefore, the most extreme scenario with perceived probabilities of 100%, very high audit costs and extreme risk aversion would at most account for $418 of forgone benefits. The average cost of itemizing in my sample is $644 and the largest amount forgone benefits is $1,400, inconsistent with an explanation based on evasion.

I calibrate the model of evasion outlined above to estimate how much of the forgone benefits it could explain. The first term of equation 1.12 is the benefit derived if the taxpayer is audited: she can only deduct the standard deduction $(T - C)$ and incurs the cost of itemizing (c) and the cost of evasion (k). It is multiplied by the probability of audit p. The second term is the benefit derived from itemizing: it is equal to the level of deductions T and is multiplied by the probability of not being audited $(1 - p)$. Overall, the sum of these two terms is equal to the expected benefit of itemizing. The right hand side of the inequality is the benefit from claiming the standard deduction. To perform the calibration, I vary p, k, and θ. I solve equation 1.12 for T, which determines the level of total deductions of a taxpayer who would stop itemizing because of evasion. I present the results of the calibration of this model in table 1.4 and 1.5 and show that for reasonable parameters, audit probabilities cannot explain the magnitude of the estimated forgone benefits. Assuming a risk aversion coefficient of 1, that an audit would cost half a day of work and that taxpayers correctly perceive audit probabilities, taxpayers would reduce their deductions by 5 to 6 dollars to avoid an audit. If the misperceive audit probabilities and believe they are 20 times what they truly are, they would forgo 102 to 114 dollars to avoid an audit. Overall, this is not consistent with the average burden I estimate of $644.

In addition, if evasion was driving the result we should observe that taxpayers who itemize - even when they are close to the standard deduction threshold - have a low proportion of deductions that are easy to evade. Mortgage interest, state and local tax deductions are hard to evade because they are third party reported to the IRS. Charitable donations however are easy to evade because they are not third party reported.[33] Figure 1.9 shows the proportion of charitable donations for taxpayers who are close to the standard deduction threshold and rejects the assumption that taxpayers switch to the standard deduction by reducing their deductions because of a fear of audit.

Finally, figure 1.7 shows an increasing relationship between income and forgone benefits inconsistent with an evasion explanation being the driver of the result.

[33] Kleven et al. (2011) show that taxpayers understand that third-party-reported deductions are harder to evade and behave accordingly.

Concave Kink Points

There is a large literature that very convincingly documents behavioral responses to features of the tax code, including and notably to kink points. This is especially important given that the empirical literature has documented that a significant portion of behavioral responses is likely to stem from deductions (rather than income for example).

Indeed, when claiming the standard deduction, taxpayers are paying the full cost of deductions. When they itemize however, they only pay a portion of it because deductions are subsidized by 1 minus the marginal tax rate. The standard deduction acts as a *concave* kink point: the price of charitable donations is lower when itemizing than when claiming the standard deduction. The indifference curve of a given taxpayer can be tangent at two points of the *concavely* kinked budget set possibly inducing some taxpayers to be indifferent between two points, one above the standard deduction and one below. Depending on the curvature of the indifference curve, this could create a bi-modal distribution with a missing mass both to the right and to the left of the standard deduction. I address this alternative explanation by performing the three following tests.

Missing Mass and Income

According to the assumption that taxpayers respond to *concave* kink points, the size of the missing mass should not respond to variations in income when controlling for the marginal tax rate. Indeed, according to this model, the only reason a taxpayer should adjust their deductions is because of the marginal tax rate and income should not matter per se in this case. On the other hand, a behavioral response due to hassle costs predicts that richer taxpayers will forgo more money because they have a higher opportunity cost of time even controlling for the marginal tax rate. Figure 1.7 graphs the relationship between forgone benefits and income - *controlling for the marginal tax rate* - and finds an increasing relationship, rejecting that taxpayers are responding to *concave* kink points in this setting.

Bounds on the Response to Concave Kink Points

Denote by T the total amount of deductions a taxpayer claims, S the standard deduction, c the proportion of charitable deductions[34] to total deductions T, τ the marginal tax rate and ϵ the elasticity of charitable donations to the marginal tax rate.

Assume that taxpayers respond one to one to a reduction in the incentives to contribute to charity.[35] Assume they are deciding between itemizing and receiving a subsidy of τ

[34]The literature has documented behavioral responses of charitable deductions to tax incentives but no responses of other deductions. The mortgage interest deduction is inert because it is based on contracts signed for long periods of time. State taxes are non-responsive because they are based on income which has been shown to be unresponsive (see for example Saez (2010) who shows that taxpayers do not adjust their income to bunch at kink points. Medical expenses are only deducted when they are in excess of 2% of income and therefore correspond to very costly procedures that are likely to be unavoidable if one wants to live.

[35]There is no consensus on what the elasticity of charitable deductions is. Andreoni (2006) in a survey of

percent or not itemizing and paying the full price of a charitable donation. The reduction in charitable donations is given by $cd\tau$. If $d - cd\tau > S$ then the taxpayer will still itemize and therefore there is no reason for them to reduce their deductions as they are still receiving the subsidy. The threshold below which taxpayers will consider reducing their deductions and claim the standard deduction is given by:

$$d = \frac{S}{1 - c\tau} \tag{1.13}$$

The standard deduction S in 1988 is equal to \$10,070, the tax rate $\tau = 0.28$, $c = 0.13$[36] and therefore an upper bound on the range below which taxpayers could exhibit a behavioral response to concave kink points is equal to $d = 10,450$. In other words, any itemizers with total deductions lower than \$10,450 will not respond to the concave kink point. If taxpayers were indeed responding to the concave kink point up to \$10,450, this will account for at most \$106 of the \$644 of forgone benefits and we would only observe a missing mass in the first bin of the distribution.

Notice that this calibrational exercise derives a generous upper bound on the behavioral response to a concave kink point. By assuming that taxpayers respond one to one to a reduction in the subsidy to donate to charity it implicitly rules out any inertia taxpayers could be subject to or any disutility taxpayers could experience from reducing their donations. This is especially important because the main identification strategy used in this paper relies on taxpayers who switch from itemizing to claiming the standard deduction.

Easy vs Hard to Adjust Deductions

In a frictionless setting where deductions can be adjusted immediately and at will - if taxpayers are responding to *concave* kink points - we would observe no taxpayers close to the standard deduction threshold. Some deductions - the mortgage interest deduction and the state tax deduction - are hard to adjust which could explain the absence of a missing mass. However, charitable donations are notorious for being among the most responsive deductions to incentives.[37] As such, if taxpayers respond to concave kink points by adjusting their deductions, one would expect that the only taxpayers who still itemize when in the neighborhood of the standard deduction would do so because they have a high proportions of hard to adjust deductions and low proportions of easy to adjust deductions. As a consequence, a *testable prediction* of this model is that we should observe that itemizers who are close to the standard deduction threshold have a low proportion of charitable deductions. This prediction is tested in figure 1.9 and ruled out. I graph the proportion of charitable donations on the y-axis as a function of the distance to the standard deduction. A behavioral response to

the literature finds price elasticities ranging from -0.08 to -1.26 and rightfully concludes that more research should be performed. As such, an elasticity of 1 seems reasonable.

[36]See figure 1.9.

[37]See for example Bakija and Heim (2011).

concave kink points predicts a steeply increasing relationship for the bins for which I observe a missing mass in figure 1.2b, followed by a plateau. Figure 1.9 rules out this pattern.[38]

Excess Mass in the Post-Reform Density

A behavioral response to a *concave* kink points leads individuals to locate away from the *concave* kink point. This mechanism is illustrated in figure 1.10. This should result in an excess mass in the post-reform density in figures 1.2a and 1.2b: as the standard deduction increases, the theory predicts that taxpayers who are close to the standard deduction are now indifferent between claiming the standard deduction and *increasing* their level of deductions. This should lead some taxpayers to increase their deductions even more implying that the post-reform density will be higher than the pre-reform one. Figures 1.2a and 1.2b show that this is not the case: the post-reform densities are always below the pre-reform ones.

Do Taxpayers Respond to Concave Kink Points?

The absence of a behavioral response to *concave* kink points is consistent with the extensive empirical public finance literature that documents behavioral responses to tax systems. In spite of the massiveness of this literature, there is not a single piece of evidence documenting such a response. Saez (2010), Kleven and Waseem (2013) and Tazhitdinova (2015) directly test the predictions of a behavioral response to both *concave* and convex kink points, find responses to convex kink points but reject any response to *concave* kink points. My results contribute to the empirical public finance literature documenting the absence of behavioral responses to *concave* kink points by showing that there is no response even in settings where friction costs are very small as is the case for charitable donations.

Rational Inattention

Could taxpayers forgo large amounts of deductions because they are uncertain of whether their total deductions are larger than the standard deductions threshold?[39]

Most of the deductions are relatively stable from year to year as they mostly consist of items that vary very little such as mortgage payments, real estate taxes or state income taxes. This means that taxpayers should have an accurate signal of their true deductions. In addition, the expenses associated with deductions are an active decision: if deductions increase or decrease by a large percentage, taxpayers are likely to be aware of this change because they caused it.

[38] The visual evidence rules out an increasing relationship and therefore rules out a response to *concave* kink points, but to address possible concerns that visual evidence is not sufficient I ran a regression of the proportion of charitable donations on the distance to the standard deduction threshold and find positive coefficients for the bins that exhibit a missing mass in figure 1.2b quantitatively and qualitatively rejecting the predictions of a response of deductions to *concave* kink points.

[39] Although in a different setting, Abeler and Jäger (2013) show that taxpayers do not seem to be rationally inattentive when responding to taxes.

Therefore, for rational inattention to explain the magnitude of the estimated hassle costs, one would need to assume that taxpayers receive a very noisy signal which is unlikely given that deductions vary little from year to year. I formalize this argument in what follows:

Assume that the taxpayer has a Constant Relative Risk Aversion (CRRA) utility function given by $U(x) = \frac{1}{1-\theta}x^{1-\theta}$ if $\theta \neq 1$ and $U(x) = \log(x)$ if $\theta = 1$.

Denote by τ the after tax amount of deductions the taxpayer can claim (deduction multiplied by marginal tax rate) and by S the after tax amount of the standard deduction. Assume that the taxpayer has beliefs over τ that follow a normal distribution with mean μ and standard deviation σ. Denote by c the cost incurred by the taxpayer to calculate the total amount of deductions τ. The cost is only incurred when she itemizes, not when she claims the standard deduction.

The taxpayer will decide to itemize if the expected benefit from itemizing given her beliefs over τ exceeds the cost of figuring out the level of τ i.e. c. This occurs when the following equation is satisfied:

$$E\left[\frac{1}{1-\theta}(\tau - c)^{1-\theta}\right] \geq \frac{1}{1-\theta}S^{1-\theta}. \tag{1.14}$$

This equation does not have a closed form solution, so I use a Taylor expansion of second degree around the mean of $\tau - c$, as follows:

$$\frac{1}{1-\theta}(\mu - c)^{1-\theta} - \frac{1}{2}\theta(\mu - c)^{-1-\theta}\sigma^2 \geq \frac{1}{1-\theta}S^{1-\theta}. \tag{1.15}$$

And for $\theta = 1$, it is equal to:

$$\log(\mu - c) - \frac{\sigma^2}{2(\mu - c)^2} \geq \log(S). \tag{1.16}$$

The first term in equation 1.16 is the expected benefit that the taxpayer derives from itemizing. The second term is a correction for the risk aversion of the taxpayer: she will itemize deductions if the benefit of itemizing corrected for her risk aversion is greater than the benefit she derives from itemizing. Holt and Laury (2002) find a θ that ranges between -0.95 and 1.37. I assume here that $\theta = 1$ (similar to Chetty (2006)) but also consider $0 < \theta \leq 2$[40] in table 1.3. I fix the standard deduction at $10,000 for joint filers. The cost estimated by the IRS of the time required to itemize deductions is $c = 149$. I can calculate a lower bound on the standard deviation of the taxpayer's beliefs over τ (σ). Using these parameters, I find that for rational inattention to explain the magnitude of the forgone benefits, the standard deviation of after tax deductions σ has to be greater than $1,814 (which corresponds to $6,479 worth of deductions with a 28% marginal tax rate). This means that the taxpayer has a range of uncertainty of deductions of more than $6,479. This implies very high uncertainty in the beliefs of the benefits that the taxpayer can save from itemizing which is unlikely given that deductions are relatively stable from year to year as they are mostly

[40] Negative values of θ are not considered because they imply risk lovingness and would trivially reject rational inattention.

constituted of mortgage payments and state taxes and are the results of active decisions. If a taxpayer's total deductions were to increase or decrease dramatically, she would most likely know about it because it would be due to for example to large income variations, the take up of a mortgage etc. which are salient.

If I assume a standard deviation of $\sigma = 200$ – which corresponds to a standard deviation of deductions of \$714 – then rational inattention with $\theta = 1$ predicts that taxpayers would claim the standard deduction up to total deductions of \$10,557 and forgo an average of \$557 worth of deductions, i.e. 156 of after tax dollars given a cost c=\$149. With reasonable parameters, rational inattention predicts that taxpayers will forgo an additional \$7 in excess of the cost of \$149.

Strategic Optimizing Behavior

Another plausible concern is that taxpayers with total deductions that are slightly smaller than the standard deduction would pool deductions from two subsequent years to pass the standard deduction threshold.

Denote by S the standard deduction amount. Assume a taxpayer whose total deductions $T = S - \epsilon$, with ϵ being a small enough amount. Assume she donates C dollars to charity every year. If $C > \epsilon$ she has an incentive to donate $2C$ in years n, $n + 2$, $n + 4$ etc and 0 in years $n + 1$, $n + 3$, $n + 5$ etc. rather than donating C every years. This would allow her to itemize in odd years and benefit from subsidized charitable donations.

First, few taxpayers switch back and forth from itemizing. In fact itemizing seems to be an absorbing state. Once taxpayers start itemizing they keep itemizing.

Second, the identification strategy used to calculate the cost relies on taxpayers switching from itemizing to claiming the standard deduction following an increase in the standard deduction. For those taxpayers total deductions T are already greater than S. So the scenario above does not even apply to them.

Other Reforms Affecting the Distribution of Deductions?

The 1988 reform

A few other changes happened in 1989. In this section, I describe these changes and explain how I adjust for the ones that are likely to affect my estimates. The estimates derived in section 1.4 already accounted for these adjustments. The fact that the pre and post-reform densities overlap away from the standard deduction threshold shows that the pre-reform density is a relevant counterfactual for the post-reform in figure 1.2a density and that – after adjusting for these changes – the missing mass estimates are not affected by these changes.

The personal interest deduction was phased out starting from 1986. In 1987, taxpayers could only deduct 65% of their personal interest, 40% in 1988 and 20% in 1989. This is likely to affect the distribution of deductions from 1987 to 1989. To control for this effect, I adjust the 1987 distribution - which is the counterfactual for 1989 - by recalculating the personal interest deduction as if only 20% of it could be deducted. This leads some taxpayers to have deductions below the standard deduction whom I drop. To ensure that there is no behavioral effect associated with the phasing out of the personal interest deduction, I compare the distribution of deductions for individuals below the 28% marginal tax rate bracket and above. If there was a behavioral effect, we should observe more deductions for individuals above the 28% marginal tax bracket. Graph **??** shows that there is no discontinuity at the marginal tax rate change at $30,950 in 1989. This is rather intuitive because the majority of the personal interest deduction is claimed for interest on student loans which are hard to adjust once they are contracted. In addition, after making this correction, I can compare the overlap between the pre and post-reform densities. Away from the standard deduction, the two graphs overlap implying that the post-reform density is an appropriate counterfactual for the 1989 density.

In 1988, the third and fourth marginal tax brackets were removed in favor of two marginal tax brackets (and a 33% rate bubble). To control for this, I only consider taxpayers who were in the 28% MTR bracket in 1987 and in 1989.

The 1971 reform

In 1970 taxpayers could claim as a standard deduction the smaller of $6130 or 10% of their income. In 1971, both thresholds were increased to $8809 or 13% of income if income is greater than $46,983, and the larger of $6166 or 13% of income for taxpayers with income smaller than $46,983.

If I were to only look at the density of itemizers above $6130 in 1970 and compare it to the density of itemizers above $8809 in 1971, my estimates would be biased because some taxpayers who have deductions greater than $8809 in 1971 are likely to stop itemizing – not because of hassle costs – but only because their deductions are now smaller than 13% of their income. To control for this, I only consider taxpayers whose deductions exceed 13% of income and $6166 in 1970. This provides an accurate counterfactual for 1971.

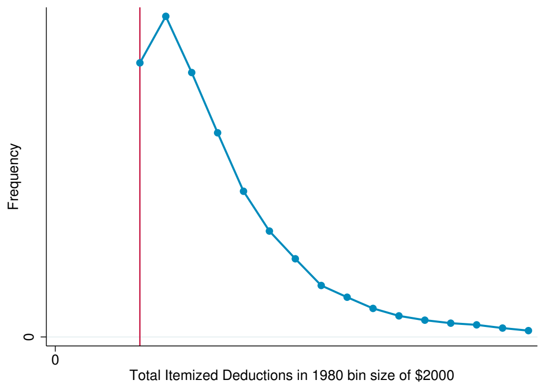
In the 1988 reform I compare the pre-reform year (1987) to the post-reform year (1989). However in this case, the standard deduction is further increased in 1972 making it impossible to compare pre and post-reform years. The 1971 reform estimates are likely to be a lower bound because they do not account for lagged responses.

1.7 Conclusion

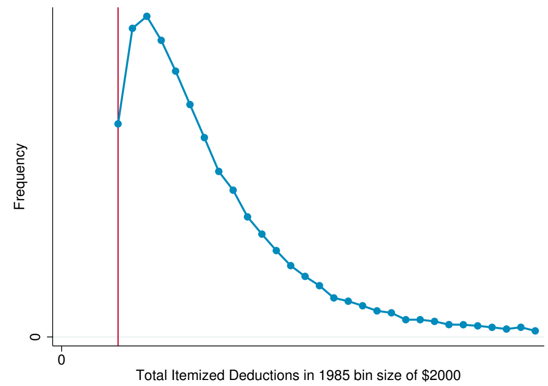
Research on the cost of tax filing has struggled with estimating the burden of tax filing. And the literature on the failure to take up government benefits has not shown that hassle costs can lead individuals to leave benefits on the table.

Using a quasi-experimental design and a novel method to recover the counterfactual density of deductions, I find that taxpayers who fail to itemize forgo large amounts of deductions, resulting in an average burden of itemizing of \$644. This implies tax filing costs of a much larger magnitude than previously estimated.

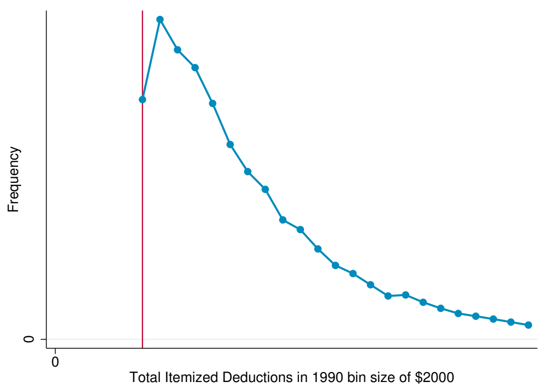
Figure 1.1: Missing Mass In the Neighborhood of the Standard Deduction



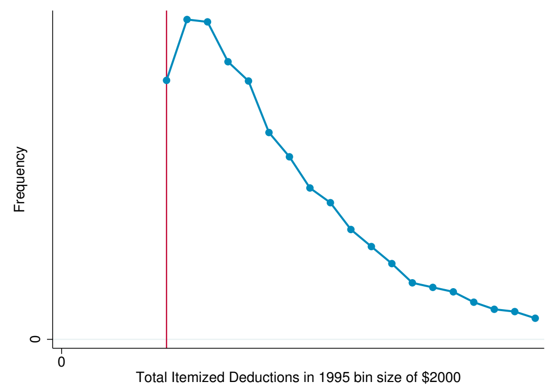
(a) 1980



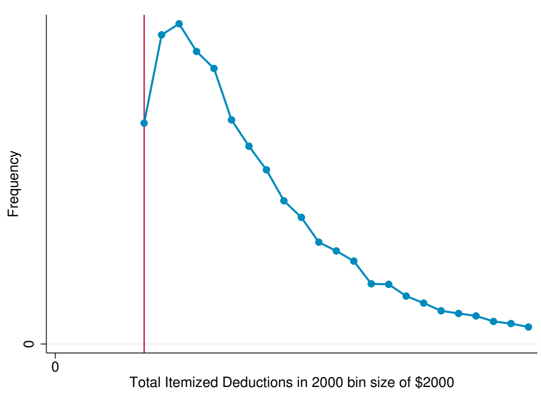
(b) 1985



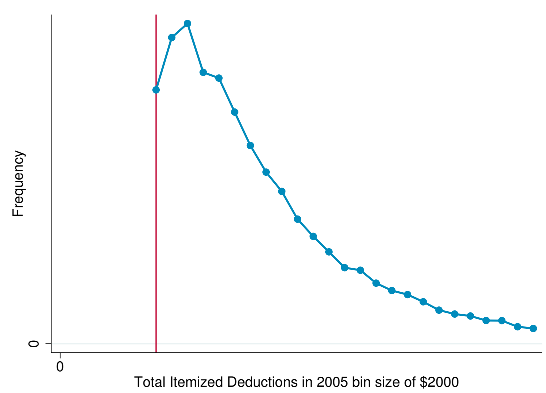
(c) 1990



(d) 1995



(e) 2000

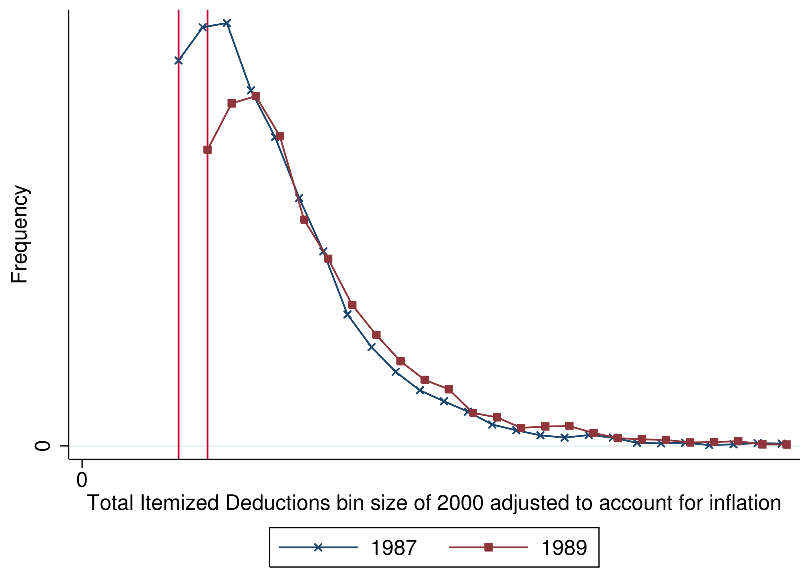


(f) 2005

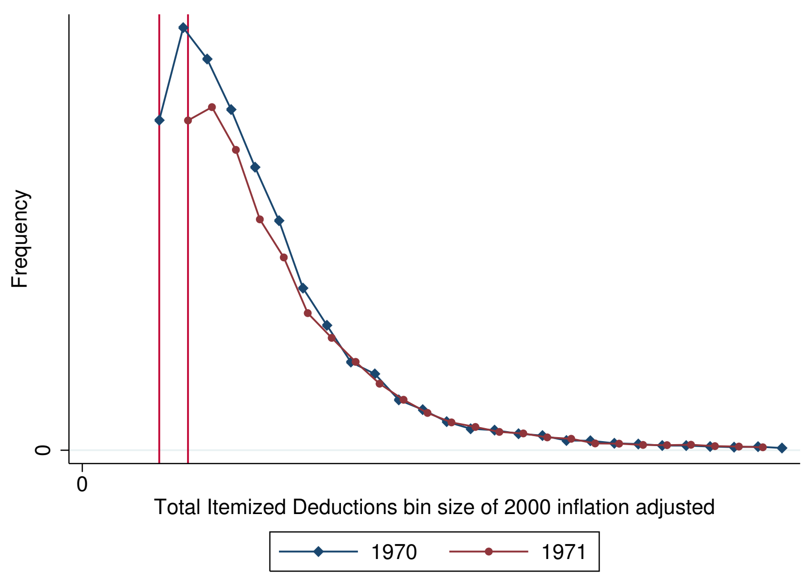
Notes: The figures above plot the density of deductions for itemizers filing jointly. The bin size is $2,000 and the vertical line represents the standard deduction threshold for each year. Notice the missing mass in the neighborhood of the standard deduction threshold. Additional years are reported in appendix figures A.2, A.3, A.4 and A.5 and figure A.6 for single filers.

Figure 1.2: Density of Deductions for Itemizers Filing Jointly Before and After the Standard Deduction Is Increased

(a) The 1988 Reform

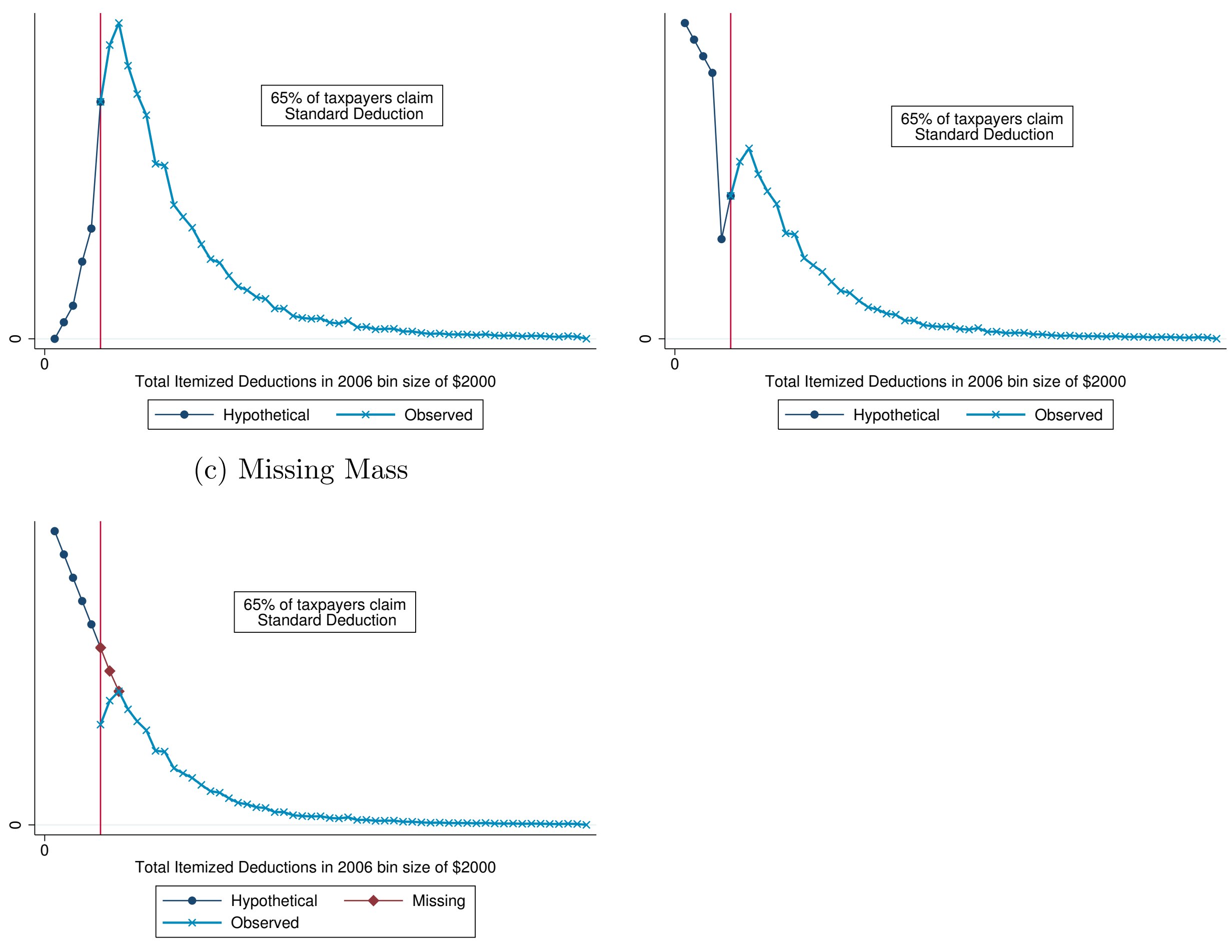


(b) The 1971 Reform



Notes: The first graph plots the density of deductions for the 1988 reform and the second one for the 1971 reform. Notice that the pre-reform density is higher than the post-reform density specifically in the neighborhood of the standard deduction, whereas the two densities are very similar when comparing them further away from the standard deduction. The statistical difference between the two densities is reported on appendix tables A.2 for 1988 and A.3 for 1971.

Figure 1.3: Different Scenarios Below the Standard Deduction



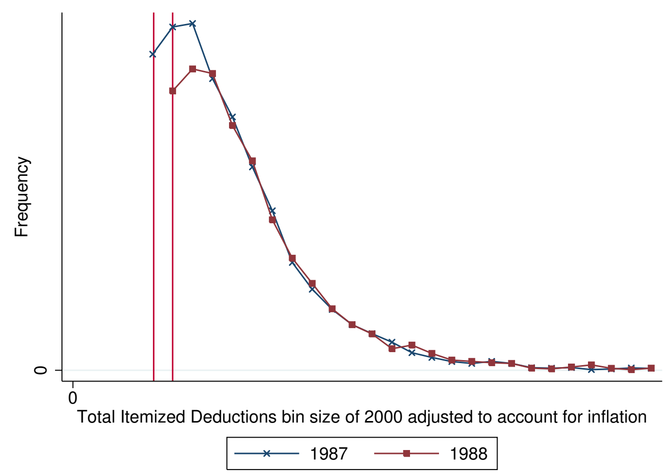
(a) Increasing: Impossible

(b) Double Peaked: Unlikely

(c) Missing Mass

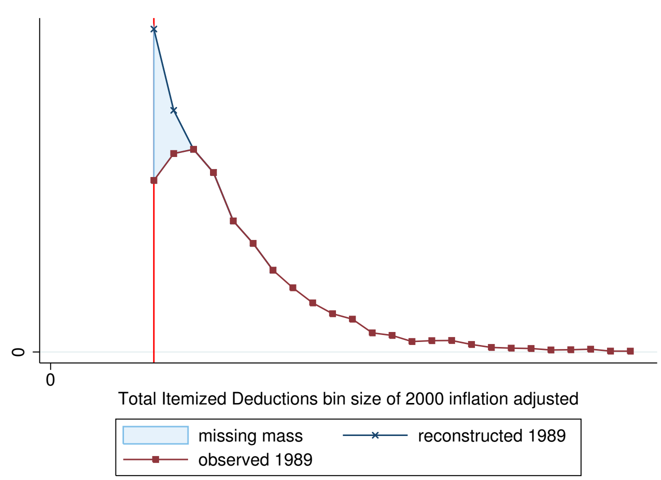
Notes: The graphs above plot the different scenarios that could be happening below the standard deduction. Graph (a) assumes that the density is strictly increasing, which is impossible given that 65% of taxpayers claim the standard deduction. This scenario would fail to account for most of the population of taxpayers. Graph (b) accounts for most of the population and is continuous at the standard deduction but the density is double peaked. This is possible but unlikely given that densities are usually single peaked. This however does not rule out densities that are double-peaked *because of the standard deduction*. Graph (c) assumes that there is a discontinuity at the standard deduction threshold because of hassle costs creating a missing mass.

Figure 1.4: Lagged Response: Small Effect During Reform Year (1987-1988)



Notes: This graph plots the distribution of deductions for itemizers filing jointly in 1987 and 1988. Notice that the missing mass is smaller than in figure 1.2a showing that there is a lagged response to the reform.

Figure 1.5: Reconstructed Density and Missing Mass in 1989

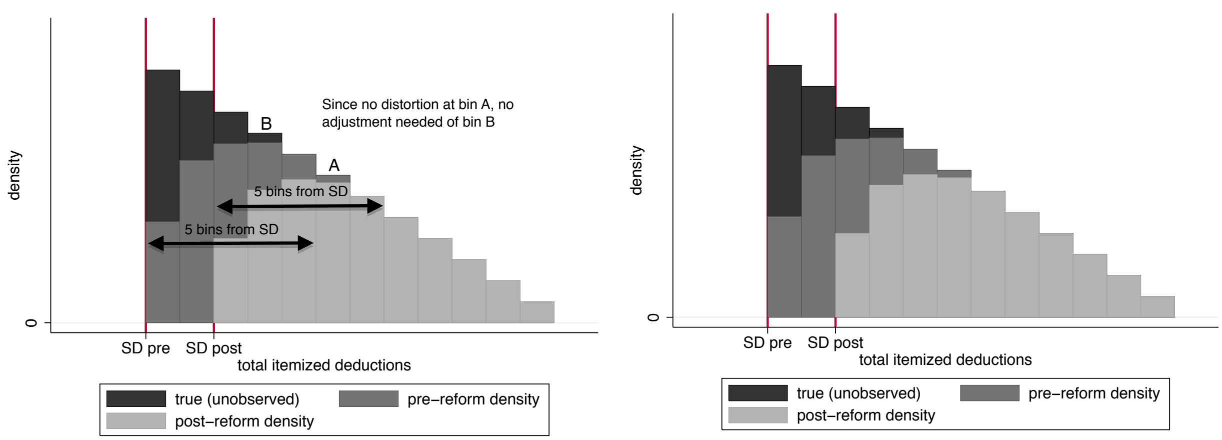


Notes: This graph plots the reconstructed density in 1989 using the method that I outline in section 1.4 and the observed density for 1989. The missing mass that allows me to estimate the burden of itemizing is given by the area lying between the two curves. The distribution of the burden of itemizing is provided in table 1.1 for a bin size of $2,000 and table 1.2 for a bin size of $1,000.

Figure 1.6: Reconstructing the Counterfactual Density

(a) No Distortion

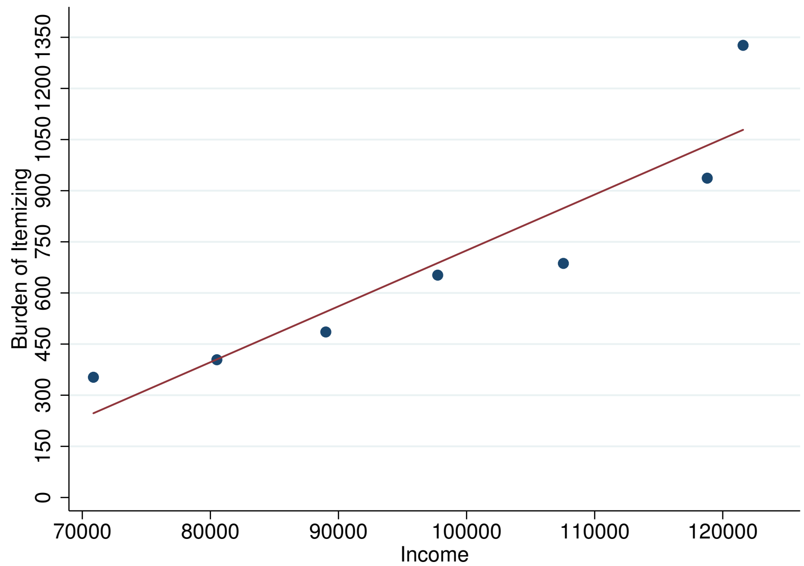
(b) Distortion



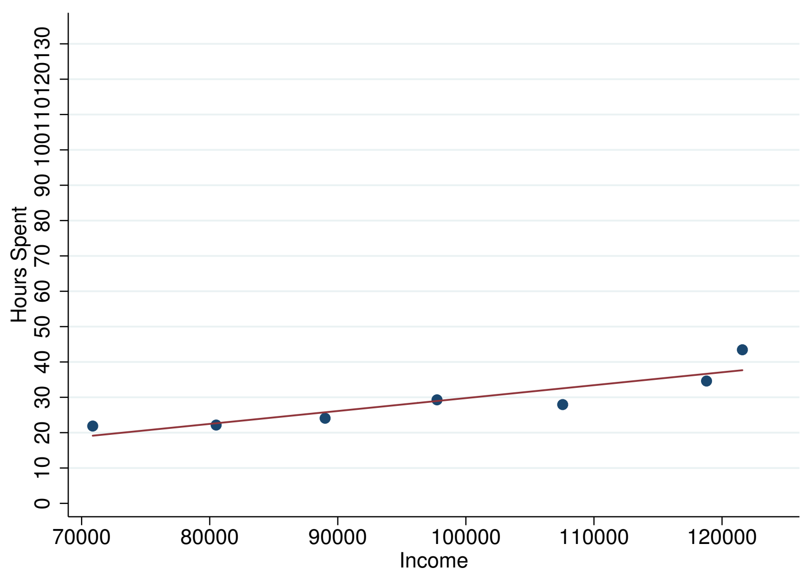
Notes: These graphs illustrate the method that I use to reconstruct the counterfactual density. The darkest histograms correspond to the true density of deductions when assuming that there is no cost. The next shade corresponds to the pre-reform year and the lightest one to the post-reform year. The vertical lines show the standard deduction threshold. In figure (a), I consider the first bin – bin A – for which the pre-reform and post-reform years overlap. There is no distortion for this bin because the two densities are overlapping. This means that 5 bins away from the pre-reform standard deduction – bin B – there should be no distortion. Which implies that 3 bins away from the post-reform standard deduction, the pre-reform density is the true density. On the other hand, in figure (b), when looking 4 bins away from the post-reform standard deduction (bin C), I find a distortion. This implies in turn that 4 bins away from the pre-reform density (bin D), there should be a distortion of equal proportion to the one that I calculated 4 bins away from the post-reform standard deduction. I adjust the density that is 2 bins away from the post-reform standard deduction – bin D – by this amount and repeat this process for all bins thereafter. This adjustment allows me to recover the true (unobserved) density.

Figure 1.7: Relationship Between Income and the Burden of Itemizing Deductions

(a) Burden of Itemizing and Income



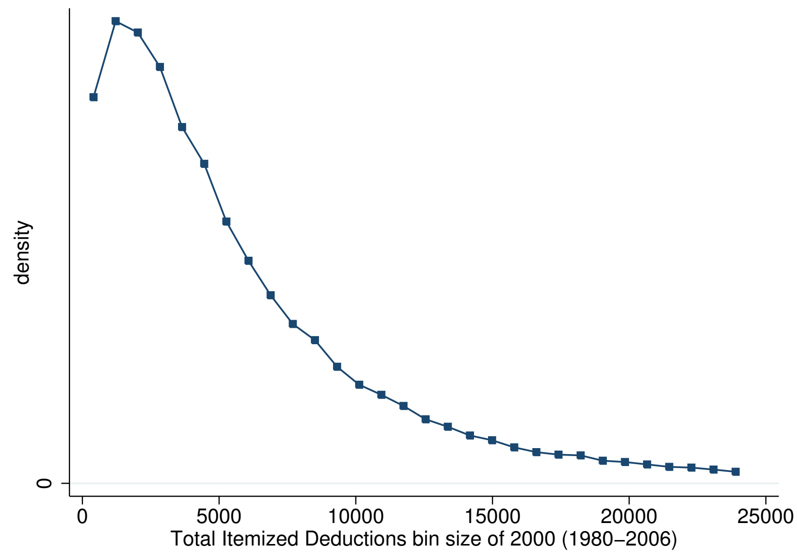
(b) Hours Spent Itemizing and Income



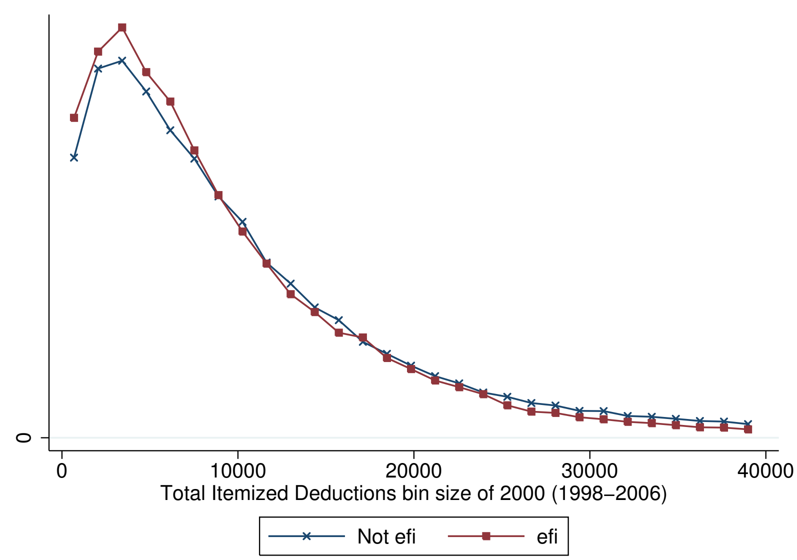
Notes: (a) The first graph shows the increasing relationship between income and the burden of itemizing: richer households are more likely to forgo deductions. This relationship controls for the variation in MTR across the different income groups. (b) The second graph divides the burden of itemizing by the hourly wage of each household and shows the implied hours spent itemizing by each income group.

Figure 1.8: Use of Tax Preparer and Electronic Filing

(a) Tax Preparer

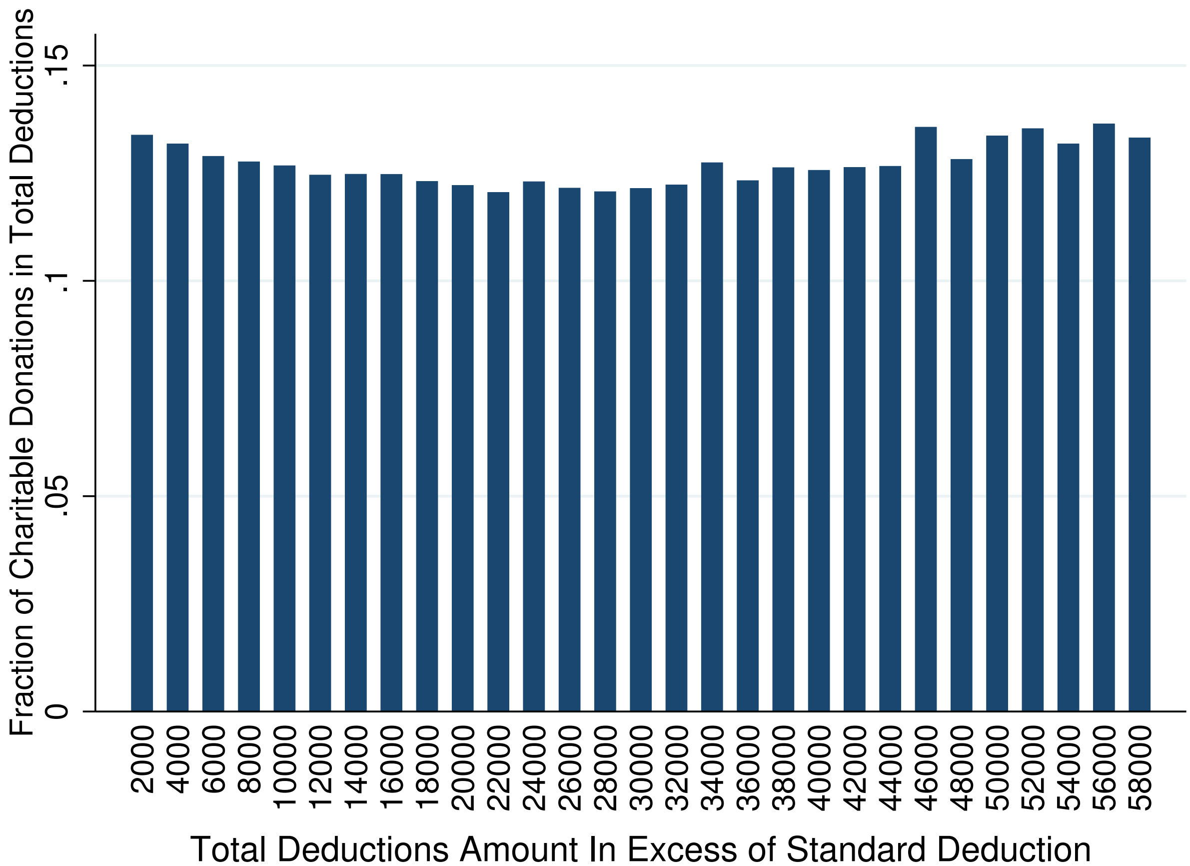


(b) Electronic Filing



Notes: Graph (a) plots the density of total deductions for taxpayers who use tax preparers from 1980 to 2006 (excluding 1985 and 1990 because the variable is not available in those years) by bin size of $2000. Graph (b) plots the density of total deductions for taxpayers who file returns electronically from 1998 to 2006 (few taxpayers used electronic filing prior to 1998) by bin size of $2000 and compares it to the density of taxpayers who do not file returns electronically. Both graphs exhibit a significant missing mass close to the standard deduction implying that neither tax preparers nor electronic filing eliminate the burden of itemizing. The use of electronic filing slightly reduces the missing mass consistent with hassle costs being the driver of the missing mass and record-keeping being the largest portion of the cost of itemizing.

Figure 1.9: Fraction of Charitable Donations in Itemized Deductions by Size of Total Deductions

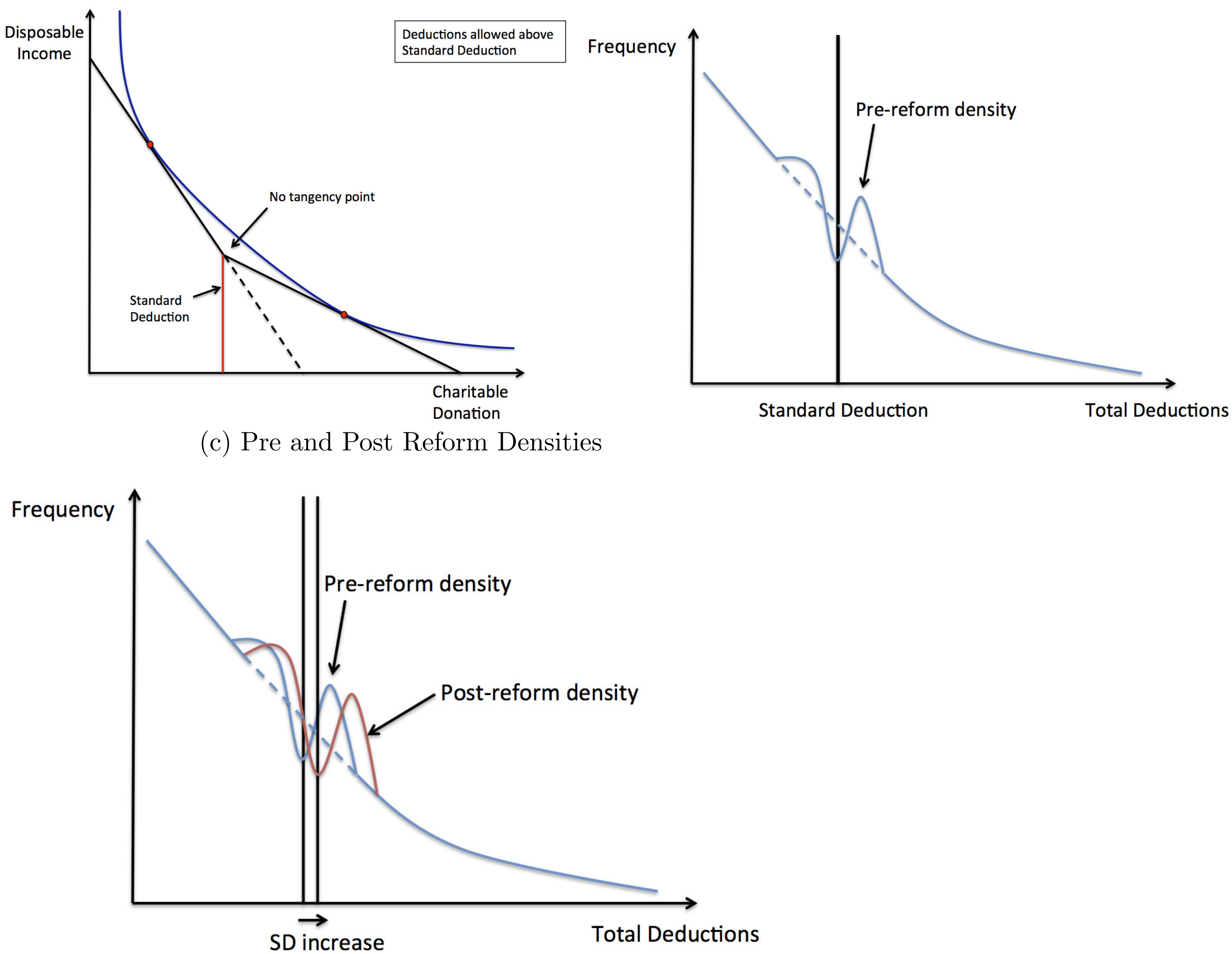


Notes: This graph shows the proportion of deductions that are charitable donations for itemizers pooling all years from 1980 to 2006 by their distance to the standard deduction. Deductions are adjusted for inflation and the standard deduction amount is subtracted from them to calculate the distance to the standard deduction. The proportion of charitable donations does not change close to the standard deduction threshold implying that taxpayers do not respond to the change in the standard deduction by reducing their charitable donations. This rules out the explanations of the missing mass based on the behavioral response to a concave kink point and evasion.

Figure 1.10: Concave Kink Point: Densities Following Reform Should Not Overlap

(a) Concave Kink Point

(b) Missing Mass Due to Concave Kink Point



(c) Pre and Post Reform Densities

Notes: Panel (a) displays a budget set with a concave kink point. Panel (b) shows the effect that a concave kink point could in theory have on the density of itemizers. Panel (c) shows that if itemizers were responding to the concave kink point, we should observe that the pre and post reform densities are not overlapping in the neighborhood of the standard deduction. This is contradicted by figure 1.2a, therefore ruling out a behavioral response to a concave kink point.

Table 1.1: Cumulative Distribution Function of the Burden of Itemizing (bin size of $2,000)

Deduction Interval (b_k)	Average Deduction	Average Benefit	CDF (p_k)	PDF (m_k)
(0, 2000]	$1000	$280	53%	53%
(2000, 4000]	$3000	$840	82%	29%
(4000, 6000]	$5000	$1400	100%	18%

Table 1.2: Cumulative Distribution Function of the Burden of Itemizing (bin size of $1,000)

Deduction Interval (b_k)	Average Deduction	Average Benefit	CDF (p_k)	PDF (m_k)
(0, 1000]	$500	$140	43%	43%
(1000, 2000]	$1500	$420	63%	20%
(2000, 3000]	$2500	$700	79%	16%
(3000, 4000]	$3500	$980	86%	7%
(4000, 5000]	$4500	$1260	100%	14%

Notes: These two tables report the Cumulative Distribution Function (CDF) and Probability Density Function (PDF) of the perceived burden of itemizing deductions. Table 1.1 uses a bin size of $2,000 and table 1.2 uses a bin size of $1,000. The first column corresponds to deductions, and the second to the after tax deductions. For example, the second row of table 1.2 corresponds to taxpayers who can save $1,000 to $2,000 of deductions, which is on average $1,500 of tax deductions and corresponds to $420 with 28% marginal tax rate. The CDF is calculated by comparing the proportion of taxpayers who itemize and those who fail to itemize. In the first row for example, 43% of taxpayers itemize implying that their perceived burden of itemizing is less than $1,000 of deductions. The average burden of itemizing is a weighted average given by the product of the average benefit and the PDF. b_k, m_k and c_k refer to the notation used in section 1.4

Table 1.3: Calibration of Rational Inattention Model

	Precision of Beliefs About Level of Savings (σ)							
	10	50	100	200	500	1000	2000	3000
CRRA coefficient								
0.1	149	149	149	150	154	177	219	301
0.25	149	149	149	151	160	193	316	501
0.5	149	149	150	153	171	235	461	774
0.8	149	149	150	154	184	283	611	1029
1	149	150	151	156	193	313	696	1164
1.1	149	150	151	157	197	328	735	1223
1.25	149	150	151	158	203	349	789	1302
1.5	149	150	152	160	213	382	868	1411
1.8	149	150	152	162	225	419	948	1513
2	149	150	153	163	233	442	993	1566

Notes: This table shows the results of a calibration of the Rational Inattention model derived in section 1.6. Rational inattention cannot explain the magnitude of the forgone benefits unless one assumes that the standard deviation of the savings is greater than $2000, which implies a standard deviation of deductions of $7,143. This corresponds to a 95% confidence interval of deductions of $\pm 14,000$, implying that a taxpayer with total deductions of $12,000 needs a 95% confidence interval equal to $[-2,000, 26,000]$ in order to forgo more than $600. Such high uncertainty is extremely unlikely given that deductions are stable and changes are usually due to active decisions on the part of the taxpayer (increase in income, take up of home mortgage etc.).

Table 1.4: Calibration of Fear of Audit Model With True Audit Probabilities

	Cost k of audit in dollars					
	50	100	150	200	250	300
CRRA coefficient						
0.5	4	4	5	6	6	7
1	5	5	6	7	7	8
1.5	5	5	6	7	7	8

Table 1.5: Calibration of Fear of Audit Model With Inflated Audit Probabilities

	Cost k of audit in dollars					
	50	100	150	200	250	300
CRRA coefficient						
0.5	88	99	110	121	132	144
1	91	102	114	127	139	152
1.5	94	106	119	132	146	160

Notes: Table 1.4 and 1.5 calibrate a model based on evasion and fear of audit. The first table assumes the true audit probabilities (1%), the second table assumes 20 times the true audit probabilities. If taxpayers are audited by the IRS, their deductions are brought back to their true level. In addition, they have to pay a cost k that includes both the hassle of an audit and the penalties they are charged. These tables show that both with the true audit probabilities and with largely inflated audit probabilities, evasion and fear of audit cannot explain the magnitude of the forgone benefits I estimate.

Chapter 2

Tax Filing Aversion or Procrastination?

Reasonable calibrations of the cost of itemizing suggest that it is unlikely that such a simple task requires so much time. Schedule A is one of the easiest forms to fill out as it does not require any complicated calculations or any tax tables. The taxpayer only needs to copy numbers from receipts and then sum them up, which is unlikely to require more than an hour of work.

Such high cost estimates could be consistent with an extreme aversion to filing taxes. Using a revealed preference argument and survey estimates of the time required to file federal taxes, I estimate that taxpayers dislike working on taxes 4.2 times more than they dislike working. If this is the case, back-of-the-envelope calculations suggest that the overall burden of filing federal income taxes is 1.28% of GDP. The policy implication of this result are that the time spent filing taxes should be reduced. This can be achieved by requiring less receipts, shortening forms and more generally simplifying the tax code.

However, there is compelling evidence that individuals are time inconsistent when saving for retirement,[1] searching for a job,[2] smoking behavior[3] and other situations. Time inconsistency introduces a wedge between hassle costs and forgone benefits.[4] A model of time inconsistency based on present bias shows that taxpayers forgo large benefits even when hassle costs are modest because they procrastinate on archiving receipts, eventually leading to large record keeping costs at the time of filing. The model makes predictions about filing time and the behavior of taxpayers close to the deadline that are consistent with evidence that I gather from tax returns.

Overall, both aversion to tax filing and naive present bias suggest that the burden of tax filing is significantly larger than previously estimated whether due to hassle costs per se or

[1] Madrian and Shea (2001).

[2] DellaVigna and Paserman (2005).

[3] Gruber and Köszegi (2001).

[4] More generally, inferring preferences from choice behavior is discussed in Koszegi and Rabin (2007), Koszegi and Rabin (2008a) and Koszegi and Rabin (2008b).

psychological biases.

2.1 Hassle Costs or Behavioral Costs?

The task of itemizing deductions imposes an average burden of $644 on taxpayers. This is a significant amount of money given the average income of the population of interest.

A revealed preference argument implies that $644 corresponds to the true hassle cost. In other words, this means that when a rational taxpayer is faced with the decision to itemize or claim the standard deduction, she will only itemize if she can save more than $644. The fact that taxpayers experience such a large disutility from itemizing could be due to an extreme aversion to filing taxes.

However, the behavioral economics literature has documented several instances in which the axiom of revealed preferences fails, in particular because of time inconsistency. A failure of this axiom introduces a wedge between forgone benefits and hassle costs, reconciling the large magnitude of my estimates with the survey evidence.

In what follows, I discuss the welfare implications of my result in light of both perspectives and argue that a model based on time inconsistency is likely to explain this behavior better than one that assumes that taxpayers are rational.

Aversion to Filing Taxes

The axiom of revealed preferences implies that taxpayers perceive the task of itemizing to be as costly as $644. This figure is calculated for taxpayers in the neighborhood of the standard deduction. Is it reasonable to assume that it is representative of the entire population of taxpayers? If the amount of deductions was randomly assigned across taxpayers, this assumption would hold. However, there is a strong relationship between deductions and income as richer taxpayers have higher state taxes, larger mortgages, more expensive houses etc. And given that richer taxpayers tend to forgo more deductions because they value their time more (as shown in graph 1.7), the average cost of $644 is likely to be a lower bound on the cost of itemizing for richer taxpayers. Taxpayers who have deductions close to the standard deduction threshold are among the poorest itemizers and therefore extrapolating the $644 of perceived costs to the entire population of itemizers is likely to understate the burden of itemizing deductions imposed on the population of itemizers. Therefore, by extrapolating this amount to the rest of the population of itemizers, I am understating the estimates of the aggregate burden of tax filing.

The IRS estimates that itemizing requires less than 4.5 hours. A revealed preference argument implies that taxpayers perceive the task of itemizing to be as costly as working 19 hours. My estimates are 4.2 times larger than the ones provided by the IRS. Their estimates are based on surveys of the time spent filing taxes. However, they do not ask how much taxpayers dislike filing taxes. If my estimates are driven by aversion to filing taxes then – taking the IRS estimates as given – my results suggest that spending an hour preparing taxes is 4.2 times more painful than spending one hour working. Taking this estimate as given, back-of-the-envelope calculations can inform us on the overall burden of filing taxes. These figures are only suggestive as I am inferring the preferences over filing taxes from taxpayers who itemize deductions who are richer than non-itemizers and not necessarily representative of the population.

If these are the true preferences of taxpayers then I can use this estimate and the survey estimates of the time required to file the various income tax forms to calculate the aggregate cost of filing taxes. If the wedge between survey estimates and revealed preference estimates is due to the aversion to filing taxes which cannot be captured by surveys, then multiplying the survey estimates by 4.2 would account for the full burden of tax filing including the aversion taxpayers experience when filing taxes. Table 2.1 shows the results of these calculations. Overall, the cost of filing federal income taxes amounts to 1.28% of GDP in 1989. In comparison, Feldstein (1999) estimates that the efficiency cost of Personal Income Tax and the Payroll Tax ranges between 2 and 5% of GDP. These orders of magnitude emphasize how important hassle costs are.

Time Inconsistency

There is extensive evidence that individuals are time inconsistent.[5]. In this section, I provide a model based on naive present bias that leads to time inconsistency and show that even small hassle costs can lead to large forgone benefits rationalizing the magnitude of my findings and the discrepancy between estimates based on revealed preferences and surveys.

Increasing Cost of Record Keeping

I assume that the cost of record keeping continuously increases for every day that the receipt is not archived as soon as it is received. When the taxpayer is issued a receipt for a charitable donation and fails to archive it, the cost of keeping track of this receipt increases continuously because it is more likely to be lost or it could take more time to look for it. The rational taxpayer archives the receipt as soon it is issued. The naive present-biased taxpayer plans on archiving the receipt but fails to do so, leading to high record keeping costs.

Assume for simplicity that the taxpayer only needs to itemize one deduction for example for a charitable contribution she made. The taxpayer is facing two distinct costs when considering the decision to itemize deductions. The first one is that of record keeping, denoted here by c. The second one is filling out Schedule A itself which is denoted by k.

If the taxpayer succeeds in performing the two tasks she receives a one time benefit b in the subsequent period. Once the taxpayer gets the receipt for her charitable contribution, she can decide to archive it immediately by incurring a cost c or archive it later and incur a

[5]In the setting of credit card debt (See Ausubel (1999)), retirement saving (See Madrian and Shea (2001)), addiction (see Gruber and Köszegi (2001)), job search (see DellaVigna and Paserman (2005)), food stamps (see Shapiro (2005)), exercise (see DellaVigna and Malmendier (2006)) and others (see DellaVigna (2009) for a survey of the literature).

larger cost $c(1+r)$ next period where r is the rate at which the cost of record keeping grows if the receipt is not archived.

δ is the time-discount factor, β the present-bias parameter, t the period in which the record keeping is performed and Schedule A is filled out and $(t+1)$ the period in benefit b is received.

In what follows, I use two definitions:

Definition 1: For given β, δ, c, k, $(1+r)$ and t a task is said to be β-worthwhile if $-c(1+r)^t - k + \beta b > 0$.

Similarly:

Definition 2 For given δ, c, k, $(1+r)$, and t a task is said to be δ-worthwhile if $-c(1+r)^t - k + \delta b > 0$.

The rational taxpayer has a standard utility function where per-period utility is discounted by δ in the future.

The decision to itemize or claim the standard deduction for the rational taxpayer can be written as follows:

$$\max_t \delta^t(-c(1+r)^t - k + \delta b),$$

conditional on itemizing being δ-worthwhile.

Cost c is incurred as soon as the taxpayer starts the record keeping. If she waits an additional t periods before archiving the receipt, the cost of record keeping is multiplied by $(1+r)$ for every additional period i.e. $(1+r)^t$ overall. Therefore, to minimize the cost of record keeping, the rational taxpayer will choose $t=0$, this means that she will archive the receipt as soon as it is received and will incur a record keeping cost of c rather than $c(1+r)^t$.

The taxpayer is left with choosing t such that:

$$\max_t \delta^t(-c(1+r)^t - k + \delta b)$$

Assume the taxpayer is contemplating the decision to perform the record keeping task in the first period yielding utility: $-c - k + \delta b$. She will only perform it if $-c - k + \delta b > 0$. And if she waits an additional period she will receive $\delta(-c(1+r) - k + \delta b)$, which is smaller than the utility she would have enjoyed if the task had been performed in the first period. This means that the rational taxpayer will either archive the receipt immediately or never archive it because she does not plan on itemizing her deductions.

The naive present biased taxpayer can perform the record keeping in period t or can wait and perform it in period $t+1$. She will prefer performing it in period $t+1$ if the following inequality is satisfied:

$$-c(1+r)^t - k + \beta b < \beta[-c(1+r)^{t+1} - k + b].$$

This inequality simplifies to:

$$-c(1+r)^t - k < \beta[-c(1+r)^{t+1} - k]. \tag{2.1}$$

A sufficient condition for equation 2.1 to hold is:

$$(1+r)\beta < 1. \tag{2.2}$$

Intuitively, for the naive present-biased taxpayer to procrastinate on archiving her receipt, it is sufficient that the rate at which the record keeping cost increases be smaller than the rate at which she discounts the future.

Provided that condition 2.1 holds in period $t = 0$, it will also hold in any subsequent period $t > 0$ i.e. if itemizing is worthwhile but not performed in the very first period, the taxpayer will procrastinate until she reaches the deadline.

Testable Prediction 1: Naive present-biased taxpayers will file their returns at the deadline of April 15th when condition 2.1 holds.

Testable Prediction 2: The cost of record keeping for naive present-biased taxpayers is greater than for rational ones. This predicts that taxpayers who file close to the deadline are likely to forgo more deductions.

Testable Prediction 1: Late Filing

The first prediction of the model outlined in section 2.1 is that naive present-biased taxpayers will bunch at the deadline when filing their taxes, consistent with the anecdotal evidence of long lines of individuals waiting at the post office on April 15th to submit their taxes.[6] Figure 2.1a graphs the volume of Google search of the term *1040* by week.[7] There is a clear spike in the weeks that include April 15th consistent with the prediction of the model and suggesting that taxpayers are naive present-biased and procrastinate on filing their taxes.

Testable Prediction 2: Late Filers Forgo More Deductions

The second testable prediction of the model outlined in section 2.1 is that taxpayers who file their returns close to the deadline are more likely to be naive present-biased (per testable prediction 1) and in turn more likely to forgo large amounts of deductions because record keeping costs are higher for them given that they procrastinate on archiving their receipts.

The SOI files contain a variable that indicates the week in which a return is processed by the IRS. Slemrod et al. (1997) have access to the internal IRS files that record the filing date and compare it to the processing date from the SOI files. They find that the order in which returns are processed matches the order in which they are filed. Knowing the order is sufficient for my purposes because what I am interested in is comparing taxpayers who file close to the deadline to those who file earlier. I can therefore use the processing time variable to identify late filers and verify the predictions of the naive present bias model. The IRS promises that returns are processed within 6 weeks. This constraint is likely to be binding

[6]Redelmeier and Yarnell (2012) for example show that there are more road crash fatalities precisely on April 15th.

[7]A similar finding has been reported by Hoopes et al. (2014) using both Google data and the volume of calls made to the IRS.

for returns that are filed close to the deadline given that a lot of returns are processed at the time. Therefore, I assume that the processing time has a lag of 6 weeks.

Consistent with the prediction that naive present-biased taxpayers are more likely to file close to April 15th and more likely to forgo deductions as shown in the previous paragraphs, I find that the density of itemizers filing in April has a larger missing mass close to the standard deduction threshold than those who file in March. Figure 2.1b shows that the density of March itemizers matches that of April itemizers except in the neighborhood of the standard deduction where there are relatively fewer April itemizers. Notice that the two densities overlap everywhere except in bins that are close to the standard deduction threshold.

I restrict the sample used to generate this graph to taxpayers who are owed refunds by the IRS and who do not have to file any other schedule but Schedule A. This allows me to rule out taxpayers who rationally delay filing to save on interest on the amount they owe to the IRS and taxpayers who cannot file early because others schedules sometimes require additional paperwork that only becomes available later in the year.

Overall, this shows that taxpayers who file late are more likely to forgo deductions, consistent with them being naive present-biased.

Note that rational taxpayers should not file close to the deadline for two reasons: by delaying filing, they forgo interest on their refunds and they expose themselves to higher filing costs. Indeed, the sample I use to generate figure 2.1b only includes taxpayers who are owed a refund by the IRS and therefore have an incentive to file as early as possible to save on interest. Second, filing costs are substantially higher closer to the deadline because lines at the post office and tax preparers are longer and it is harder to get tax help from the IRS because their phone lines are very busy.

Notice also that late filing is hard to reconcile with the option value of waiting for low cost realizations. One could argue that taxpayers who bunch at the deadline are rational taxpayers who wait for a low cost realization and face a series of idiosyncratic shocks that force them to file hastily at the very last moment and lead them to forgo benefits. If that is the case, then we should observe that taxpayers who file late in year t are equally likely to file earlier in year $t + 1$. To test for this, I graph the average week in which returns are processed in year $t + 1$ by week of processing in year t, in figure 2.2. If taxpayers who bunch at the deadline are doing so for rational reasons, the relationship should be constant as we should observe mean reversion. If they are doing so because of a systematic bias, the relationship should be increasing as year t week of processing should predict year $t + 1$ week of processing. Figure 2.2 shows an increasing relationship between processing week in year t and year $t + 1$ consistent with the explanation that late filing is due to a systematic bias.

Bound on Record Keeping Costs

At any point in time, taxpayers have access to tax preparers. For a given sum of money, the taxpayer can get a tax specialist to fill out her 1040 and Schedule A forms. However, the tax preparer cannot perform the record keeping for her. The tax preparer fee provides an upper bound on the cost of filling out Schedule A for the taxpayer: if the cost of filling out Schedule A is larger than the fee, she can go to a tax preparer.

I can identify this fee in the dataset: individuals who itemize their deductions are allowed to deduct the tax preparer fee from their income. The average tax preparer fee for individuals who file the 1040 and Schedule A but not Schedule B, C, D etc. is $220. This is the fee for filling out both the 1040 form and Schedule A, submitting the documents and helping with audits if the need arises. This means that $220 is a generous upper bound. If the burden of itemizing deductions is driven by the cost of filling out Schedule A then taxpayers have the outside option of paying someone to perform this task and - for some of them - save large sums of money. This suggests that any cost in excess of $220 should be attributed to record keeping. Since the estimated cost is equal to $644, the record keeping cost accounts for more than 64% of the burden of itemizing.[8] This is consistent with taxpayers having large record keeping costs.

Hassle Costs When Taxpayers Are Naive Present Biased

I use the difference in size of the missing mass for taxpayers who file in March versus taxpayers who file in April to estimate the proportion of the forgone benefits that is due to taxpayers being naive present-biased and the proportion that is due to the cost of filing that would be incurred by rational taxpayers.

Calculations based on figure 2.1b show that rational filers forgo $417 less than naive present-biased taxpayers. According the IRS survey, it is rational not to itemize if one saves less than $149. This means that naive present bias explains 84% of the forgone benefits in addition to the $149.

The difference between the estimated hassle costs when assuming full rationality and when assuming time inconsistency emphasizes the importance of accurate behavioral modeling when drawing welfare implications. If taxpayers are rational then the estimated cost distribution is the true hassle cost. On the other hand, if taxpayers are naive present-biased, then a portion of the burden of itemizing deductions is not due to hassle costs per se but due to the time inconsistency of taxpayers.

This is important in two ways. First, it draws different conclusions about the magnitude of hassle costs. Second, it calls for different policy interventions. If taxpayers are rational, then the only possible intervention is to reduce true hassle costs (less record keeping, less forms etc.). If they are time inconsistent, interventions that specifically target the bias itself should also be considered.

In table 2.2, I calculate the aggregate cost of filing taxes assuming taxpayers are naive present-biased using the parameters derived above. The costs of filing taxes when the taxpayer is assumed to be naive present-biased amounts to 0.5% of GDP versus 1.28% if we assume that forgone benefits are only due to rational behavior.

[8]This is consistent with Slemrod and Bakija (2008) who use survey evidence to argue that most of the burden of filing taxes is due to record keeping.

2.2 Policy Implications

Cost of Filing Taxes

Policy makers have no precise estimates of the burden of filing taxes. Most of the literature on the cost of filing taxes is based on survey evidence (Slemrod and Sorum (1984) and Blumenthal and Slemrod (1992b)). Taxpayers are only surveyed about the time they spend working on taxes but not on the disutility it causes them. To my knowledge, this is the first paper to use a non-parametric approach along with administrative data to reveal the preferences of taxpayers over the cost of filing taxes. The tax filing burden is large, suggesting that the welfare lost because of hassle costs is substantial and of policy importance. The cost is also distortionary as it impacts individuals differently: it varies with income, type of deductions etc. which can raise equity concerns.

Addressing Hassle Costs

If taxpayers are averse to filing taxes and if preferences are indeed driving the result, the only available policy instrument is a direct reduction of the cost. This can be achieved by reducing the complexity of the tax system, having less deductions, less credits etc.

Addressing Time Inconsistency

With naive present-biased taxpayers, the model derived in section 2.1 shows that the policy intervention should not necessarily target the collection process itself but rather the behavior of the individual. In light of my evidence, a policy that would aim at reducing the cost of filling out forms seems misguided since the majority of the cost is precisely due to record keeping. One approach could be to require less evidence of expenses when the taxpayer itemizes. This would prove out to be efficient in reducing hassle costs but is likely to result in more evasion. The policy maker has to trade off the cost that evasion imposes on society and the cost that filing taxes imposes on individuals. Tazhitdinova (2014) explores this tradeoff in the case of charitable donations.

The model derived in section 2.1 also shows that there are relatively inexpensive policy interventions that can significantly reduce the cost of filing taxes. Advocates of pre-populated forms argue that they are likely to reduce evasion and mistakes by taxpayers. My results show that pre-populated forms are also likely to improve welfare by reducing hassle costs. Two of the three most common deductions are mortgage interest payments and state and local income taxes. Both are third-party reported implying that the IRS knows the amount of deductions that the taxpayer qualifies for. Gillitzer and Skov (2013) show that the introduction of pre-populated forms in Denmark increases claimed deductions consistent with the fact that taxpayers fail to claim deductions for expenses they incurred because of hassle costs. Kotakorpi and Laamanen (2013) show that pre-populated deductions increase but non pre-populated deductions decrease in Finland with the introduction of pre-populated forms.

The use of electronic receipts is another channel through which record keeping costs can be further reduced. Some employers issue form W2 online and some banks provide an electronic 1098. Keeping track of an electronic document can be much easier than a paper one. However, this would only benefit taxpayers who have access to the Internet possibly creating further inequalities.

Given that taxpayers tend to procrastinate on filing their taxes and wait until April 15th, potentially facing a large cost of itemizing on that day, the policymaker can ensure that the deadline for filing taxes falls on a day when people are likely to be less busy such as the weekend. The IRS actually has the opposite policy: if April 15th is a weekend day, the deadline is postponed to the next Monday. This was probably relevant when e-filing was not available and taxpayers had to visit the post-office to send their returns, but less relevant now with the prevalence of e-filing.

To address the issue of the increasing marginal disutility of labor, the IRS can have two deadlines: one on April 15th for the 1040 form and one a week later for Schedule A. Having only one deadline can result in the taxpayer filing all her taxes on the same day, but having two allows the naive present-biased taxpayer to smooth effort over time. This policy would help naive present-biased taxpayers but would not hurt rational ones as they would still be able to file their taxes on the same day if they want to. Similarly, the IRS could also coordinate with local governments to ensure that the deadlines for state and federal taxes do not overlap.

Naive present bias justifies shifting the burden of filing taxes from individuals to firms. Firms are less likely to be subject to psychological biases. For example, in the case of charitable donations, requiring charitable organizations to report donations and then having the IRS send a statement to taxpayers (or pre-populate Schedule A) will result in less hassle costs on aggregate because firms are less likely to be time inconsistent and more likely to have a system of information that deals with receipts in a systematic way.

Should Hassle Costs Be Reduced?

Kaplow (1998) argues that some hassle cost can be efficient when designing a tax system. The social gains of deductions are unclear and some advocate that they are relatively small.[9] If political economy concerns prevent the government from repealing these deductions, one way of ensuring that taxpayers do not claim them is to impose significant hassle costs.

Screening Literature

There is a long tradition in public economics that emphasizes the benefits of conditioning transfers on fixed characteristics and more particularly imposing transaction costs when providing welfare to screen out richer households. To my knowledge there was no empirical evidence confirming that hassle costs are larger for richer households. The results in this

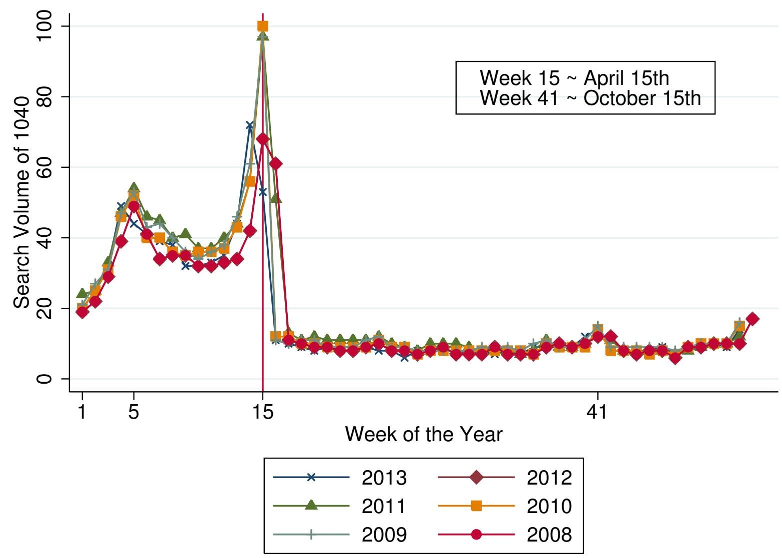
[9] See Slemrod and Bakija (2008) for example.

paper show that it is the case and that such policy can be efficient. It warns however that transaction costs need to be chosen with care as they can be relatively large and can end up screening out more income groups than optimal. They can also screen out naive present-biased taxpayers versus rational ones rather poor taxpayers versus poorer ones.[10]

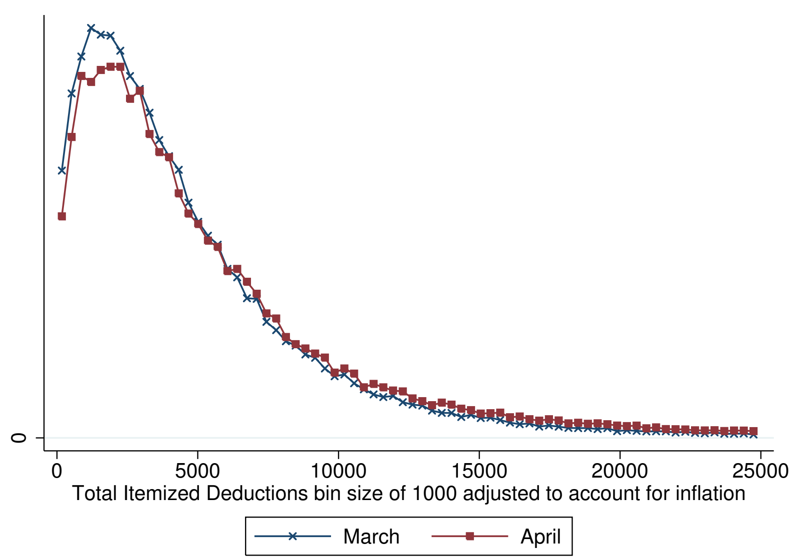
[10] This has been suggested in Bertrand et al. (2006) and in Congdon et al. (2009) for example.

Figure 2.1: Deadline Effects

(a) Google Search of the Term 1040

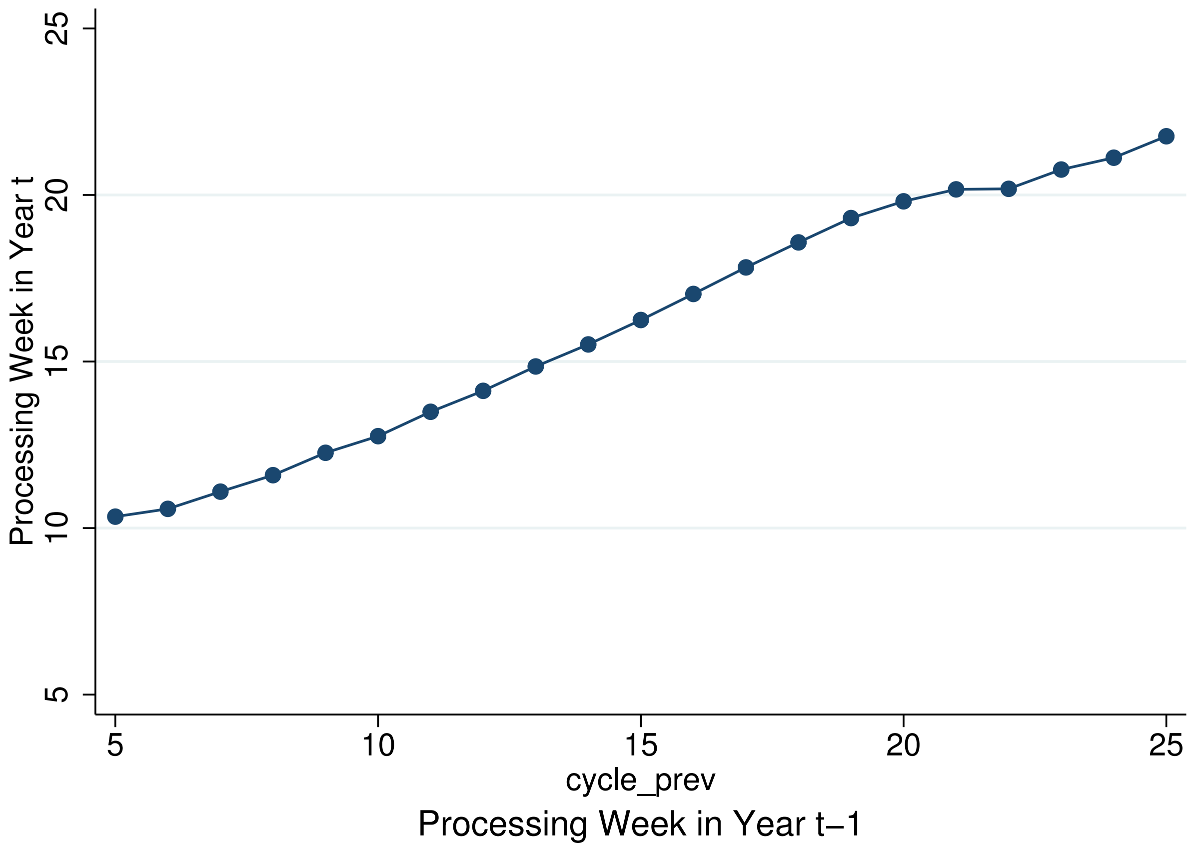


(b) March Itemizers v.s. April Itemizers



Notes: The first graph plots the volume of search of the term "*1040*" in Google. The x-axis is in weeks. April 15th typically falls in week 15, while August 15th – which corresponds to the filing extension deadline – falls in week 41. Notice the spike in search on week 15 and the spike in week 41 consistent with the prediction of the naive present-bias model that time inconsistency leads taxpayers to file at the last moment. The second graph plots the density of itemizers who file their returns in March and the density of those who file in April. The dataset is constituted of 20 repeated cross section (1980 to 1999: years in which the variable is available) pooled together. Consistent with the prediction of the naive present-bias model, April filers tend to forgo more deductions in the neighborhood of the standard deduction than March filers.

Figure 2.2: Processing Week in Year t v.s. Year $t-1$



Notes: This graph plots the average week in which a return is processed in year t on the y-axis and the average week in which a return is processed in year $t-1$ on the x-axis. The relationship is increasing implying that taxpayers who file late in year $t-1$ are more likely to file late in year t consistent with the predictions of the naive present-bias model.

Table 2.1: Aggregate Burden of Filing Taxes Assuming Taxpayer Is Rational

Form	Hours (from IRS)	Hourly Wage (in $)	Tax-Aversion Coefficient	Individual Burden (in $)	Nb. of Taxpayers (million)	Aggregate Burden (in $b.)	% of GDP
1040	9.40	17.69	4.32	718.90	0.11	80.52	0.74
Sch. A	4.53	34.70	4.32	679.37	0.03	21.74	0.20
Sch. B	1.28	22.26	4.32	123.13	0.01	1.53	0.01
Sch. C	9.63	22.12	4.32	920.62	0.01	12.89	0.12
Sch. D	3.75	37.05	4.32	600.48	0.01	5.12	0.05
Sch. E	5.83	35.67	4.32	898.71	0.01	12.76	0.12
Sch. F	16.10	21.43	4.32	1491.05	0.00	3.52	0.03
Sch. SE	1.13	17.00	4.32	83.05	0.01	0.96	0.01
Total						**139**	**1.28**

Table 2.2: Aggregate Burden of Filing Taxes Assuming Taxpayer Is Naive Present-Biased

Form	Hours (from IRS)	Hourly Wage (in $)	Tax-Aversion Coefficient	Individual Burden (in $)	Nb. of Taxpayers (million)	Aggregate Burden (in $b.)	% of GDP
1040	9.40	17.69	1.69	281.36	0.11	31.51	0.29
Sch. A	4.53	34.70	1.69	265.88	0.03	8.51	0.08
Sch. B	1.28	22.26	1.69	48.19	0.01	0.60	0.01
Sch. C	9.63	22.12	1.69	360.30	0.01	5.04	0.05
Sch. D	3.75	37.05	1.69	235.01	0.01	2.00	0.02
Sch. E	5.83	35.67	1.69	351.73	0.01	4.99	0.05
Sch. F	16.10	21.43	1.69	583.55	0.00	1.38	0.01
Sch. SE	1.13	17.00	1.69	32.50	0.01	0.38	0.00
Total						**54.4**	**0.5**

Chapter 3

Should I Stay Or Should I Go? The Migration Patterns of High-Skilled Workers: Evidence From Alumni Databases.

3.1 Introduction

The migration patterns of highly educated and highly skilled workers can have large effects on the economy. Modern theories of endogenous growth emphasize the importance of highly skilled workers and the consequences of their migration patterns on growth.[1] In addition, highly skilled individuals can be costly to educate, implying that migration can lead to high burdens for the origin country with no substantial benefits. This is particularly true for most of the European countries where education is provided for free both in high school and in college. Migration is also of policy importance: if workers are relatively mobile, they are likely to leave for countries that offer them the best economic environment.

There is however little empirical evidence on the migration patterns of highly skilled workers originating from developed countries. This lack of evidence is especially surprising given the interest of policy makers and the general public in this issue. Indeed, one of the main arguments against raising taxes is based on the idea that it will lead high skilled individuals to flee to other states or countries with lower tax rates. Newspaper articles tend to adopt polarized views on the topic, some claiming that this is a well known and prevalent phenomenon[2] and some arguing the opposite.[3] This issue has also been the subject of tumultuous public debates and has led to a plethora of newspaper articles documenting

[1]See for example Lucas (1998), Bhagwati and Hamada (1974), Piketty (1997) or Haque and Kim (1995).

[2]See *Sorry New York Times, Tax Flight of the Rich Is Not a Myth* in Forbes.

[3]See *The Myth of the Rich Who Flee From Taxes* in the New York Times.

instances in which high skilled individuals leave their countries of origin because of heavy bureaucracy,[4] lack of funding due to budget cuts,[5] low salaries,[6] etc.

Except for anecdotal evidence, little is known about the emigration patterns of high skilled individuals from their countries of origin. This is mostly due to the lack of data that can be used to track the locations of individuals over time. Past research has relied on survey evidence[7] or focused exclusively on immigration for which it is easier to obtain data using work visa or permanent residence applications.[8]. In this paper, I use a novel dataset to study the migration of high skilled individuals: alumni databases of graduates from leading post-secondary institutions in France. This dataset has the advantage of being updated yearly and is used by the vast majority of alumni implying very low attrition rates and high precision.

The series show a steady decline in the proportion of individuals living in France from a high of 95% in 1944 to a low of 66% in 2004. The trend has been increasing ever since 2004, reaching 75% in the most recent year. This recent increase is to be contrasted with the national debate in France arguing that high skilled individuals are fleeing the country because of high taxes and bleak economic prospects. The Great Recession had no significant effect on this steady increase of individuals deciding to remain in France possibly because graduates of these schools can easily find jobs even in times of recession.[9]

This paper contributes to the empirical migration literature by showing that alumni databases can be used to study the migration patterns of high skilled workers and track their locations over time going back to the early 1950's. By using similar datasets in different countries and institutions, researchers can precisely address questions that have been left unanswered so far due to lack of data.[10] Most studies have used country specific data that studies inflow migration but no studies have been able to address outflow migrations.

This paper also contributes to a recent policy debate in France on the attractiveness of the country and its ability to retain its most talented workers. Some have argued that entrepreneurs and high skilled workers are fleeing France because of increasing taxes and high administrative burdens. I show that the proportion of high skilled workers leaving France has been steadily increasing with a recent decreasing trend, contradicting the opinion that there has been a massive exodus in recent years.

[4]See *Au Revoir, Entrepreneurs* in the New York Times.

[5]*America's Top Young Scientists Warn of Systemic Brain Drain: Colleagues 'Sort of Disappear'* in the Huffington Post.

[6]See *French Professor Finds Life In U.S. Hard to Resist* in the New York Times.

[7]Which suffers from large attrition rates likely to bias the results. See for example:

[8]See for example

[9]Statistics issued by these schools claim that 98% of graduates find a job within 3 months of graduation.

[10]These include for example the migration response to taxation, the effect of borders on mobility or the effect of the mobility of high skilled individuals on growth.

3.2 Data and Institutional Background

Institutional Background

The French post-secondary system is composed of two separate and very different types of institutions: Universities and *Grandes Ecoles*.[11] Universities function in a very similar way to Universities in most other countries: education is mostly free, admissions are almost universal, classes are large etc. *Grandes Ecoles* are a particularity of the French education system. They were created with the explicit goal of forming the French elites and have been successful at doing so: the vast majority of French top politicians, researchers and CEOs hold degrees from these schools.

Admission into *Grandes Ecoles* is competitive. There are three types of *Grandes Ecoles* that prepare for three types of careers: Engineering, Business and Research. After graduating from High School, students enroll in two year classes - called *Classes Preparatoires*[12] - with the only goal of preparing them to the entrance exams to the *Grandes Ecoles*. At the end of the two years, students take written and oral exams in several disciplines[13]. Their rankings in these exams then determine which *Grandes Ecoles* they are accepted into. The vast majority of the highest ranked individuals choose the highest ranked *Grandes Ecoles*. Acceptance rates are very low[14] and each year, less than 500 students are admitted in each of the leading *Grande Ecole*. Because all exams are in French and the majority of *Classes Preparatoires* are located in France, these schools accept very few foreign nationals. In 2012 for example, of the 4.752 students who took the exam for the leading business school, 132 students were coming from foreign *classes preparatoires* of which one was eventually admitted.

In this paper I consider individuals who graduated from the highest ranked Business school – HEC Paris – and the highest ranked Engineering school – Ecole Polytechnique.

Data

The database used in this paper is based on two separate datasets. Each dataset is created by the alumni association of each of the two schools. The alumni associations request from each school the name and program of each student of a graduating cohort. This information is then stored in the database. Every year, students are required to renew their membership to the alumni association. In doing so, they provide an address to which a physical copy of the alumni database can be shipped. In addition, they can report their work or home address as well as their phone number and past and current employment on a voluntary basis. This information can then be used by other alumni for networking purposes. The engineering

[11] Literally translated as "Great Schools".

[12] Literally translated as Preparatory Classes

[13] Mathematics, Physics, French Literature, Philosophy, Foreign Languages, History, Geography, Biology and Chemistry.

[14] Less than 8% conditional on taking the entrance exam.

school database also provides information about the date at which the information was last changed and the country of citizenship of each graduate (reported by the school to the alumni association).

The name, cohort and program of each graduate is comprehensive: every person who graduates from one of these two schools will have this information recorded irrespective of whether they are members of the alumni network. Because the alumni network is widely used by students for networking, most of them are also members and therefore communicate their address. This is the address that I use to identify the location of each graduate.

3.3 Results

Increased Migration

Figure 3.1 and 3.2 and tables 3.1, 3.2 and 3.3 consistently show that the proportion of graduates of top French universities who leave France has been steadily increasing. Virtually all business school alumni from the 1940's and 1950's cohorts remained in France. This proportion has dropped below 70% in 2003, 2004 and 2005. The location of engineering graduates has followed similar trends: close to 90% of the 1984 cohort remained in France, whereas this proportion has decreased to close to 70% for recent cohorts.

There is a notable increase in the proportion of graduates remaining in France starting from the mid 2000's. This increase is particularly strong for business school alumni, increasing from 68% in 2006 to 77% in 2011. There has been an increase in the engineering graduates remanning in France in recent years as well, but it is much more modest.

This phenomenon could be explained by an increase in the general attractiveness of France in recent years, although it is not clear what could have triggered this. However, it is worth emphasizing that there has been a heated debate in France about an hemorrhage of high skilled individuals in recent years. My findings show that recent years have seen an *increase* in the number of graduates remaining in France, settling the debate.

Countries of Emigration

The country that attracts most French graduates is the United Kingdom. In 2005 – when the proportion of business graduates remaining in France was at its lowest – the UK accounted for 29.6% of emigrants, as can be seen in table 3.2. As a single country, the US comes second. The rest is mostly composed of neighboring - Spain, Italy, Belgium, Germany and Luxembourg - and Asian countries. Notice from figure 3.1 that the increase in business graduates remaining in France after 2005 mostly comes from individuals not emigrating to the UK, US and Asian countries. The proportion of individuals emigrating to neighboring countries was not affected. The location of Engineering graduates who emigrate from France is similar to business graduates: they mostly leave to the UK, the US is second as a single country but neighboring countries account for a larger share than the US.

Figure 3.3 shows that business alumni are relatively more mobile than engineering alumni. This might be due the specificities of the French system of education, where studying foreign languages is not as emphasized in engineering schools as much as in business schools. In addition, business schools tend to admit more foreign students than engineering schools. If they tend to go back to their countries of origins, this could be an additional explanation. This difference in mobility seems to have converged in the most recent years, following the increase in the proportion of graduates remaining in France.

Countries of Origin

The engineering alumni database allows me to observe the country of origins of graduates. The school lists the citizenship(s) of each alumni. Figure 3.4 and table 3.4 show the time series of the location of *French* native engineering alumni. Comparing figure 3.4 to 3.2, we can see that French citizen alumni are *even more* likely to leave France than foreign nationals who come to study in France. The proportion of French citizens remaining in France has been relatively stable from 1984 to 2011, approximately equaling 75%. This implies that a substantial part of the variation across time in figure 3.2 is driven by the location decisions of foreign born alumni. The majority of them remained in France in the mid to late 1980's, but progressively started leaving afterwards.

Their main country of destination is the UK. We can see this in table 3.8. They are more likely to remain in France then go abroad, but if they do leave France, they are most likely to go to the UK, and closely followed by the US. The UK is a natural destination for foreigners who graduate from France because the French job market requires knowledge of French. Although table 3.9 shows that the two largest nationalities are Moroccan and Tunisian which are both former French colonies and where most people speak fluent French, there is a large contingent coming from Brazil, China and Vietnam which is less likely to speak French and more likely to leave for the UK. The close proximity of Paris to London, the fact that London is the largest financial center in Europe and the fact that the French job market requires proficiency in French naturally explain that London attracts a lot of alumni both French nationals and foreign born. The large dominance of the US and the UK cannot be explained by foreign alumni returning to their home countries, as table 3.9 shows that there are very few Americans and British alumni.

The country to which French citizen graduates emigrate to the most is the United States, as can be seen in figure 3.4. The attractiveness of the US has increased substantially in the early 1990's. In recent years, they account for approximately 50% of the French national engineering alumni leaving France from Ecole Polytechnique.

3.4 Using Alumni Databases to Study the Migration of High Skilled Individuals

Advantages of Alumni Databases

Studying the migration patterns of individuals across countries is difficult for lack of good dataset. It is even more difficult to study the migration patterns of high skilled individuals. Within country migration has been traditionally studied using survey data[15] and more recently using administrative tax data[16]. Studying international migration is complicated by the fact that there is no international survey data and using tax data is not accurate as it is likely that a substantial number of individuals will attempt to evade taxes by reporting locations in tax advantaged countries. In addition, the majority of countries do not tax individuals based on their citizenship but rather on their location. French nationals – for example – living abroad do not report their taxes to France and their location would not be recorded in tax data. Alumni databases on the other hand are able to track individuals over their entire lifetime and accurately provide their locations. In this paper, I only used one cross section of all cohorts, but it is possible with additional work to recover all cross sections and match each individual to previous cross sections and precisely track their locations over time, essentially creating a panel data of their entire work locations. In addition to that, these databases also include additional demographics such as the name of the workplace, industry of employment, sometimes even marital status and number of children.

Shortcomings

Alumni databases are not perfect. They are a hybrid of administrative and survey datasets in that they contain the universe of alumni, but alumni are the ones who update information about themselves in these databases. Contrary to survey datasets however, alumni have a strong incentive to keep their information up to date. But there are still some missing information for some alumni. Tables 3.1 and 3.2 show that 6.89% of the business school alumni do not report their location. Table 3.3 shows that this proportion is equal to 7.7% for engineers. These attrition figures are low, given that the dataset contains the universe of alumni graduating from these schools. Overall, these datasets provide relatively good coverage and are the only ones to date we can use to study the migration of high skilled individuals.

Questions that can be studied

Alumni databases can be used to document the migration patterns of high skilled individuals and study how attractive a given country is relative to others as was done in this paper.

[15]See for example Blanchard et al. (1992)

[16]See for example Yagan (2014), Chetty et al. (2013) or Chetty and Hendren (2015).

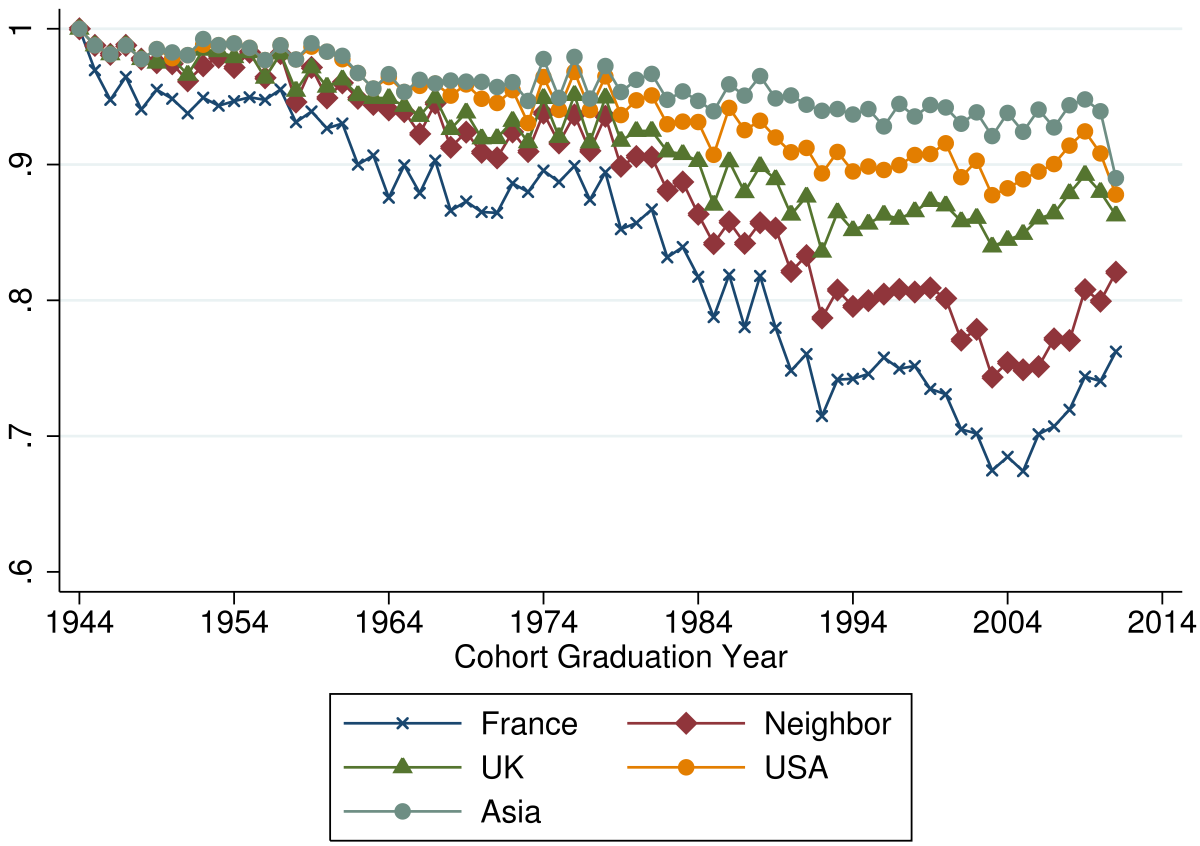
Additional questions can be answered using these datasets. The Public Finance literature does not know whether people are willing to emigrate to pay lower taxes. Kleven et al. (2013) and Kleven et al. (2014) have documented this phenomenon in very specific cases, namely soccer players and immigration to Denmark, but there is no general and systematic evidence on the behavioral response of (high-skilled) individuals to taxes through migration. Using alumni databases from different countries to build a panel data of the flows of high skilled individuals along with large tax reforms can be used to answer this question convincingly.

Several other questions can be answered using these databases. For example we do not know how shocks to the economy affect international mobility, in the spirit of Blanchard et al. (1992) and Yagan (2014), but at the international level.

3.5 Conclusion

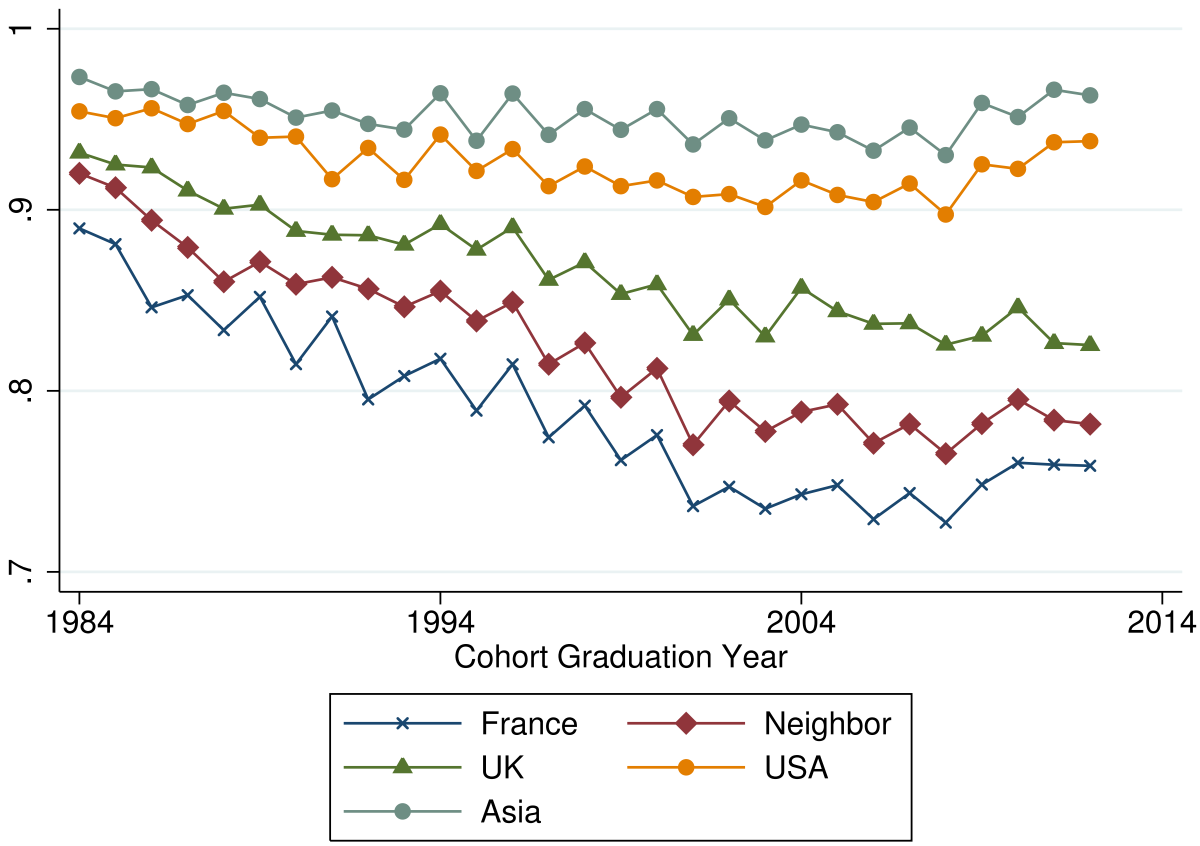
This paper advances the international migration of high skilled individuals literature in two ways. First, it documents the migration patterns of high skilled graduates from France, settling a heated debate that they have been fleeing France over the past decade. Second, it is meant as a proof of concept that alumni databases can be studied to answer questions we were unable to study for lack of good sources of data.

Figure 3.1: Location of Business Graduates from 1944 to 2011



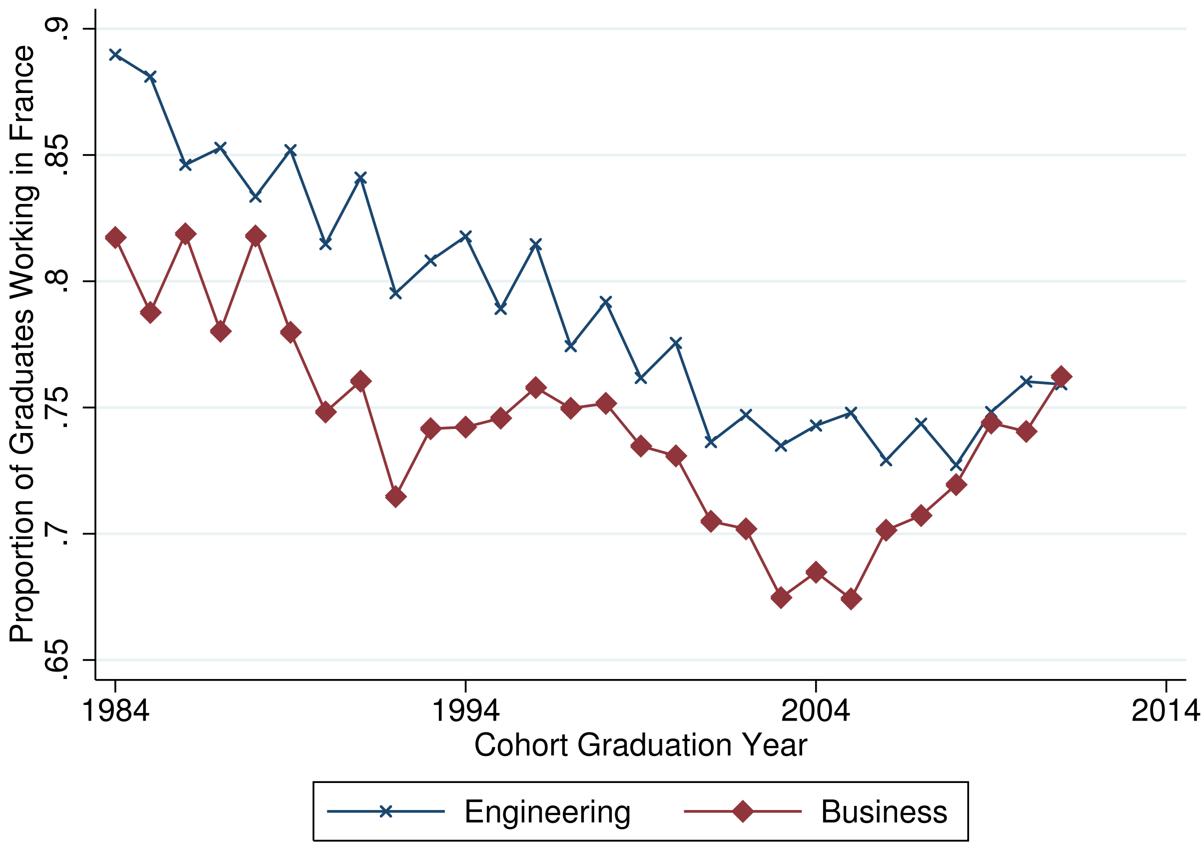
Notes: This graph plots the time series of business school graduates from 1944 to 2011 by their country of destination. The series are constructed by taking a two-year moving average.

Figure 3.2: Location of Engineering Graduates from 1984 to 2011



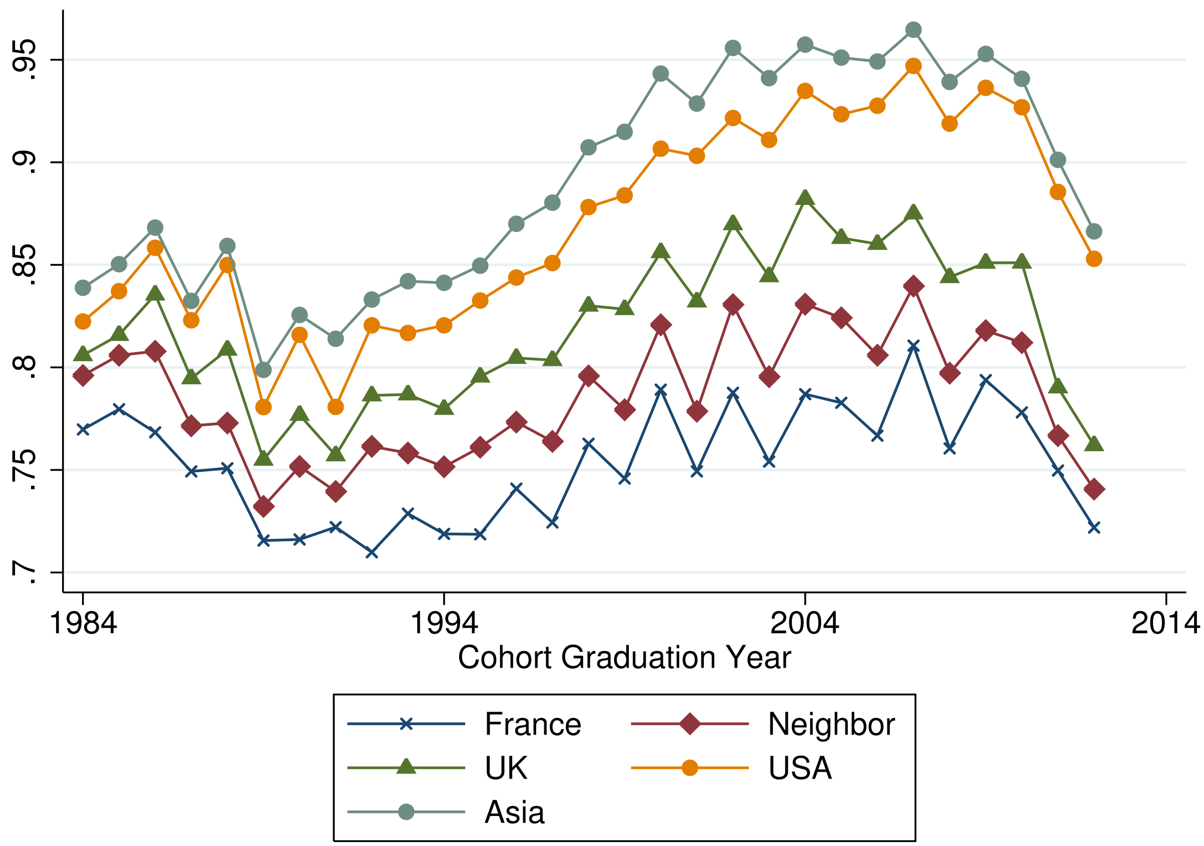
Notes: This graph plots the time series of engineering school graduates from 1984 to 2011 by their country of destination. The series are constructed by taking a two-year moving average.

Figure 3.3: Proportion of Alumni Who Remain in France



Notes: This graph plots the time series of engineering and business school graduates from 1984 to 2011 who remain in France. The series are constructed by taking a two-year moving average.

Figure 3.4: Location of Engineering Graduates from 1984 to 2011: French Nationals



Notes: This graph plots the time series of engineering school graduates who are French nationals, from 1984 to 2011 by their country of destination. The series are constructed by taking a two-year moving average.

Table 3.1: Location of Business School Graduates 1944-1979

Cohort Year	France	United Kingdom	United States	Neighbors	Asia	Missing	Total
1944	26	0	0	0	0	10	36
1945	34	0	0	1	0	20	56
1946	77	0	0	3	0	40	122
1947	97	0	0	4	0	42	144
1948	101	0	0	1	0	42	144
1949	80	0	0	3	0	37	123
1950	92	0	2	3	0	16	116
1951	116	1	0	2	1	22	142
1952	107	1	1	2	0	36	148
1953	123	2	1	4	0	27	159
1954	122	0	0	7	0	24	155
1955	150	0	2	3	0	29	185
1956	150	0	1	2	0	19	174
1957	141	0	2	2	0	26	177
1958	165	0	1	7	0	27	202
1959	169	3	6	3	0	26	208
1960	188	0	5	5	1	25	226
1961	197	0	4	6	0	25	238
1962	185	1	1	7	0	55	255
1963	189	1	3	15	0	42	258
1964	199	1	2	9	0	54	278
1965	205	3	4	14	1	26	260
1966	234	1	3	10	0	17	274
1967	194	3	6	6	1	42	262
1968	197	1	2	10	0	51	271
1969	193	3	5	15	4	40	267
1970	210	6	8	14	1	33	280
1971	242	2	10	6	2	31	306
1972	181	1	4	5	4	36	242
1973	199	2	2	12	1	30	253
1974	200	2	2	8	3	29	256
1975	204	3	5	7	5	16	243
1976	201	0	7	5	1	27	252
1977	223	4	3	11	0	19	267
1978	206	3	4	12	3	15	256
1979	233	3	5	10	4	15	277

Notes: This table reports the number of Business School alumni by cohort and their most likely locations as well as the number of missing locations by year.

Table 3.2: Location of Business School Alumni 1980-2011

Cohort Year	France	United Kingdom	United States	Neighbors	Asia	Missing	Total
1980	238	7	6	12	6	13	293
1981	221	7	7	16	4	17	285
1982	259	4	9	10	3	11	304
1983	239	9	4	11	6	15	300
1984	232	8	5	18	10	9	301
1985	238	14	13	16	3	4	303
1986	235	9	17	14	9	11	312
1987	239	12	10	7	7	9	293
1988	223	13	10	22	6	9	295
1989	251	13	10	17	13	14	330
1990	235	8	8	21	11	12	313
1991	198	12	17	26	12	2	284
1992	246	20	15	25	9	6	338
1993	264	20	20	19	18	5	368
1994	288	21	17	22	14	5	393
1995	265	20	11	19	12	9	359
1996	278	22	15	19	18	6	377
1997	330	26	15	17	13	8	443
1998	252	15	13	22	14	8	344
1999	277	22	18	26	10	7	379
2000	259	30	11	30	11	7	367
2001	332	36	20	33	12	12	475
2002	301	40	15	21	21	7	443
2003	318	40	19	38	21	5	468
2004	288	44	18	39	17	9	446
2005	312	43	16	26	30	5	462
2006	333	48	19	29	15	9	492
2007	337	58	16	20	12	12	480
2008	348	41	16	33	11	7	487
2009	340	44	17	28	16	12	485
2010	347	38	14	27	11	8	463
2011	404	36	11	31	15	16	546

Notes: This table reports the number of Business School alumni by cohort and their most likely locations as well as the number of missing locations by year.

Table 3.3: Location of Engineering Alumni 1984-2012

Cohort Year	France	United Kingdom	United States	Neighbors	Asia	Missing	Total
1984	234	3	5	8	5	46	304
1985	222	5	5	14	3	44	299
1986	240	3	8	8	3	35	304
1987	247	12	9	10	3	28	311
1988	234	12	10	6	3	58	330
1989	237	11	18	4	3	56	335
1990	239	3	7	5	9	62	331
1991	208	5	7	17	3	37	287
1992	221	8	8	6	12	45	306
1993	237	11	15	15	5	49	341
1994	261	11	12	14	4	47	356
1995	277	9	14	8	10	50	373
1996	278	15	16	18	9	45	396
1997	289	15	16	17	10	32	391
1998	289	16	21	13	14	22	387
1999	313	12	22	9	13	14	398
2000	289	22	22	13	10	11	388
2001	312	16	18	16	16	5	395
2002	300	20	34	10	10	10	398
2003	311	15	23	18	11	4	398
2004	301	19	19	23	14	7	399
2005	317	26	19	17	7	5	401
2006	322	12	29	10	8	5	397
2007	289	17	34	14	10	14	390
2008	320	16	28	13	6	7	395
2009	312	20	25	15	6	11	401
2010	304	10	39	6	7	17	391
2011	305	11	35	12	5	15	392
2012	270	8	34	7	5	40	374

Notes: This table reports the number of engineering alumni by cohort and their most likely locations as well as the number of missing locations by year.

Table 3.4: Location of French Native Engineering Alumni 1984-2012

Cohort Year	France	United Kingdom	United States	Neighbors	Asia	Missing	Total
1984	234	3	6	8	5	50	313
1985	228	5	6	16	3	55	322
1986	246	4	8	9	3	46	328
1987	254	12	13	11	3	32	335
1988	240	14	13	6	3	68	356
1989	242	12	19	5	3	59	351
1990	242	4	8	5	9	67	345
1991	225	5	11	20	3	51	332
1992	224	9	9	7	12	49	325
1993	248	13	18	16	5	52	366
1994	268	12	13	17	4	54	387
1995	285	11	14	8	10	56	393
1996	290	16	18	18	8	53	428
1997	297	19	17	17	12	37	416
1998	307	20	22	13	14	22	418
1999	328	16	25	10	13	17	427
2000	306	26	26	15	11	16	425
2001	335	24	24	22	21	9	455
2002	326	26	40	14	14	14	464
2003	344	27	29	21	17	12	475
2004	316	20	23	23	18	11	435
2005	358	38	27	22	12	7	489
2006	364	27	36	17	13	12	497
2007	337	25	37	18	15	24	495
2008	358	27	39	20	17	9	495
2009	351	32	31	18	16	23	498
2010	348	19	50	12	15	35	493
2011	365	16	41	15	11	32	499
2012	330	19	49	10	11	67	502

Notes: This table reports the number of French native engineering alumni by cohort and their most likely locations as well as the number of missing locations by year.

Table 3.5: Countries of Emigration: Business School Alumni, 1944-2011

Country	Nb. Alumni	Country	Nb. Alumni	Country	Nb. Alumni
Algeria	7	Germany	138	Panama	1
Andorra	1	Georgia	1	Paraguay	1
Argentina	17	Greece	13	Peru	2
Armenia	1	Guinea	1	Philippines	2
Austria	22	Hungary	7	Poland	14
Australia	42	India	26	Portugal	10
Bahamas	1	Indonesia	4	Romania	3
Bahrain	1	Ireland	15	Qatar	7
Belgium	162	Israel	22	Russia	18
Benin	2	Italy	76	Saudi Arabia	4
Brazil	61	Ivory Coast	13	Senegal	14
Brunei	1	Jamaica	1	Serbia	4
Burundi	1	Japan	54	Sierra Leone	1
Burkina Faso	2	Jordan	2	Singapore	72
Cambodia	2	Kazakhstan	3	Slovakia	4
Cameroun	7	Kuwait	1	Slovenia	1
Canada	73	Laos	1	South Africa	9
Chile	9	Lebanon	50	South Korea	11
China	213	Lithuania	1	Spain	165
Colombia	10	Luxembourg	92	Sweden	6
Congo	7	Madagascar	6	Switzerland	294
Costa Rica	1	Malaysia	12	Taiwan	4
Croatia	3	Mali	1	Thailand	10
Cuba	2	Mauritius	4	Timor-Leste	1
Cyprus	1	Mexico	33	Trinidad	1
Czech Republic	17	Monaco	21	Turkey	14
Denmark	9	Morocco	126	Tunisia	28
Dominican	2	Mozambique	2	UAE	66
Egypt	6	Netherlands	38	United Kingdom	827
Ethiopia	1	New Caledonia	1	United States	533
Finland	3	New Zealand	1	Ukraine	5
France	14,353	Nigeria	1	Venezuela	8
Gabon	2	Norway	18	Vietnam	8

Notes: This table shows the countries of emigration of business school alumni.

Table 3.6: Countries of Emigration: Engineering Alumni, 1944-2011

Country	Nb. Alumni	Country	Nb. Alumni	Country	Nb. Alumni
Algeria	7	Germany	138	Panama	1
Andorra	1	Georgia	1	Paraguay	1
Argentina	17	Greece	13	Peru	2
Armenia	1	Guinea	1	Philippines	2
Austria	22	Hungary	7	Poland	14
Australia	42	India	26	Portugal	10
Bahamas	1	Indonesia	4	Romania	3
Bahrain	1	Ireland	15	Qatar	7
Belgium	162	Israel	22	Russia	18
Benin	2	Italy	76	Saudi Arabia	4
Brazil	61	Ivory Coast	13	Senegal	14
Brunei	1	Jamaica	1	Serbia	4
Burundi	1	Japan	54	Sierra Leone	1
Burkina Faso	2	Jordan	2	Singapore	72
Cambodia	2	Kazakhstan	3	Slovakia	4
Cameroun	7	Kuwait	1	Slovenia	1
Canada	73	Laos	1	South Africa	9
Chile	9	Lebanon	50	South Korea	11
China	213	Lithuania	1	Spain	165
Colombia	10	Luxembourg	92	Sweden	6
Congo	7	Madagascar	6	Switzerland	294
Costa Rica	1	Malaysia	12	Taiwan	4
Croatia	3	Mali	1	Thailand	10
Cuba	2	Mauritius	4	Timor-Leste	1
Cyprus	1	Mexico	33	Trinidad	1
Czech Republic	17	Monaco	21	Turkey	14
Denmark	9	Morocco	126	Tunisia	28
Dominican	2	Mozambique	2	UAE	66
Egypt	6	Netherlands	38	United Kingdom	827
Ethiopia	1	New Caledonia	1	United States	533
Finland	3	New Zealand	1	Ukraine	5
France	14,353	Nigeria	1	Venezuela	8
Gabon	2	Norway	18	Vietnam	8

Notes: This table shows the countries of emigration of engineering school alumni.

Table 3.7: Countries of Emigration: French Engineering Alumni, 1984-2012

Country	Nb. Alumni	Country	Nb. Alumni	Country	Nb. Alumni
Algeria	3	Indonesia	6	Peru	4
Argentina	6	Iran	1	Philippines	4
Australia	19	Ireland	3	Poland	7
Austria	5	Israel	18	Portugal	6
Bahrain	1	Italy	20	Qatar	3
Belgium	90	Japan	45	Reunion	1
Bermuda	1	Kazakhstan	2	Romania	14
Brazil	59	Kenya	2	Russia	20
Cambodia	1	Korea	1	Scotland	1
Cameroon	2	Kuwait	2	Senegal	16
Canada	72	Lebanon	10	Singapore	73
Chile	11	Libya	2	Slovakia	3
China	133	Luxembourg	14	Spain	46
Colombia	2	Madagascar	1	Sweden	18
Congo	3	Malaysia	5	Switzerland	157
Czech	4	Mali	1	Taiwan	2
Denmark	10	Mauritania	1	Thailand	4
Ecuador	5	Mauritius	2	Tunisia	43
Egypte	1	Mexico	6	Turkey	2
Fidji	1	Missing	1039	UAE	25
Finland	1	Monaco	1	UK	501
France	8596	Morocco	82	USA	672
Gabon	2	Netherlands	14	Ukraine	2
Germany	85	Niger	1	Uruguay	3
Hungary	3	Nigeria	2	Vietnam	22
India	7	Norway	11		

Notes: This table shows the countries of emigration for engineering school alumni.

Table 3.8: Countries of Emigration of Foreign Engineering Alumni 1984-2012

Country	Nb. Alumni	Country	Nb. Alumni
Argentina	1	Luxembourg	3
Australia	2	Madagascar	1
Belgium	4	Malaysia	1
Bermuda	1	Mauritania	1
Brazil	37	Mexico	2
Canada	20	Missing	218
Chile	8	Morocco	72
China	28	Norway	4
Congo	2	Poland	2
Denmark	2	Portugal	1
Ecuador	5	Qatar	2
Egypte	1	Romania	7
France	618	Russia	5
Gabon	1	Senegal	6
Germany	11	Singapore	22
Hungary	2	Spain	19
India	3	Sweden	5
Indonesia	2	Switzerland	26
Iran	1	Tunisia	41
Israel	1	UAE	12
Italy	4	UK	138
Japan	4	USA	120
Kazakhstan	1	Uruguay	2
Korea	1	Vietnam	18
Lebanon	8		

Notes: This table shows the countries of emigration for foreign national engineering school alumni.

Table 3.9: Engineering Alumni By Nationality 1984-2011

Citizenship	Nb. Alumni	Citizenship	Nb. Alumni	Citizenship	Nb. Alumni
Algerian	9	French British	3	Kazakh	2
American	5	French Canadian	6	Korean	3
American Taiwanese	1	French Chiliean	5	Lebanese	30
Argentinian	1	French Congolese	1	Lebanese Swiss	1
Australian	1	French Dutch	2	Lithuanian	1
Austrian	1	French Ecuadorian	1	Luxembourger	3
Belarusian	1	French German	7	Malawian	1
Belgian	2	French Iranian	4	Malaysian	3
Beninese	1	French Italian	3	Malgasy	2
Brazilian	72	French Lebanese	11	Mauritian	1
Brazilian Italian	2	French Malgasy	1	Mexican	5
Brazilian Portuguese	1	French Mexican	1	Missing Citizenship	286
British	4	French Moroccan	38	Moldavian	1
British Iranian	1	French Peruvian	1	Monacoian	2
British Moroccan	1	French Polish	2	Moroccan	199
Bulgarian	4	French Romanian	11	Moroccan Portuguese	1
Burkinabe	1	French Russian	13	Norwegian	3
Cambodian	2	French Senegalese	1	Peruvian	2
Cameroonian	22	French Serb	1	Polish	4
Canadian	16	French Spaniard	1	Romanian	58
Chilean	20	French Swedish	1	Russian	34
Chinese	122	French Swiss	5	Russian Ukrainian	1
Colombian	1	French Tunisian	22	Senegalese	18
Costa Rican	1	French Turkish	2	Singaporeans	7
Croatian	1	French Vietnamese	5	Spaniard	29
Dutch	2	Gabonese	3	Swedish	6
Ecuadorian	7	German	12	Swiss	4
Egyptian	1	Greek	3	Syrian	1
Ethiopian	1	Hungarian	4	Taiwanese	1
French	10,588	Indian	2	Tunisian	128
French Algerian	7	Indonesian	3	Turkish	2
French American	16	Iranian	21	Ukrainian	3
French Armenian	1	Irish	1	Uruguayans	2
French Belarusian	1	Italian	9	Venezuelans	1
French Belgian	2	Ivorian	8	Vietnamese	103
French Brazilian	5	Japanese	2		

Notes: This table shows the countries of origin of engineering alumni.

Bibliography

Abeler, Johannes and Simon Jäger, "Complex Tax Incentives-An Experimental Investigation," American Economic Journal: Applied Microeconomics, 2013, p. Forthcoming.

Andreoni, James, "Philanthropy," Handbook of the economics of giving, altruism and reciprocity, 2006, 2, 1201–1269.

Ausubel, Lawrence M., "Adverse Selection In the Credit Card Market," Working Paper, University of Maryland 1999.

Bakija, Jon and Bradley T Heim, "How Does Charitable Giving Respond To Incentives And Income? New Estimates From Panel Data.," National Tax Journal, 2011, 64 (2 Part 2), 615–650.

Bertrand, Marianne, Sendhil Mullainathan, and Eldar Shafir, "Behavioral economics and marketing in aid of decision making among the poor," Journal of Public Policy & Marketing, 2006, 25 (1), 8–23.

Bhagwati, Jagdish and Koichi Hamada, "The Brain Drain, International Integration of Markets for Professionals and Unemployment: a Theoretical Analysis," Journal of Development Economics, 1974, 1 (1), 19–42.

Bhargava, Saurabh and Day Manoli, "Why Are Benefits Left On the Table? Assessing the Role Of Information, Complexity, and Stigma On Take-Up With an IRS Field Experiment," Working Paper 2011.

Blanchard, Olivier Jean, Lawrence F Katz, Robert E Hall, and Barry Eichengreen, "Regional evolutions," Brookings papers on economic activity, 1992, pp. 1–75.

Blank, Rebecca M. and David E. Card, "Recent Trends in Insured and Uninsured Unemployment: Is There an Explanation?," The Quarterly Journal of Economics, 1991, 106 (4), 1157 – 1189.

Blumenthal, Marsha and Joel Slemrod, "The compliance cost of the US individual income tax system: A second look after tax reform," National Tax Journal, 1992, pp. 185–202.

_ and _ , "The Compliance Cost of the US Individual Income Tax System: A Second Look After Tax Reform," *National Tax Journal*, 1992, pp. 185 –202.

Chetty, Raj, "A new method of estimating risk aversion," *The American Economic Review*, 2006, pp. 1821–1834.

_ and Nathaniel Hendren, "The Impacts of Neighborhoods on Intergenerational Mobility: Childhood Exposure Effects and County-Level Estimates," *Working Paper*, 2015.

_ , John N Friedman, and Emmanuel Saez, "Using Differences in Knowledge across Neighborhoods to Uncover the Impacts of the EITC on Earnings," *American Economic Review*, 2013, *103* (7), 2683–2721.

Congdon, William J, Jeffrey R Kling, and Sendhil Mullainathan, "Behavioral Economics and Tax Policy," *National Tax Journal*, 2009, *62* (3), 375.

Currie, Janet, "The Take Up of Social Benefits," *NBER working paper 10488*, 2004.

DellaVigna, Stefano, "Psychology and Economics: Evidence from the Field," *Journal of Economic Literature*, 2009, *47* (2), 315 –372.

_ and M Daniele Paserman, "Job Search and Impatience," *Journal of Labor Economics*, 2005, *23* (3).

_ and Ulrike Malmendier, "Paying Not to Go to the Gym," *The American Economic Review*, 2006, pp. 694 –719.

Duclos, Jean-Yves, "Modelling the take-up of state support," *Journal of Public Economics*, 1995, *58* (3), 391–415.

Engström, Per, Katarina Nordblom, Henry Ohlsson, and Annika Persson, "Tax compliance and loss aversion," *American Economic Journal: Economic Policy*, 2013, p. Forthcoming.

Ericson, Keith M. Marzilli, "Forgetting We Forget: Overconfidence and Memory," *Journal of the European Economic Association*, 2011, *9* (1), 43 –60.

Feenberg, Daniel and Jonathan Skinner, "Sources of IRA Saving," *Tax Policy and the Economy*, 1989, pp. 25 –46.

Feldstein, Martin, "Tax Avoidance and the Deadweight Loss of the Income Tax," *Review of Economics and Statistics*, 1999, *81* (4), 674 – 680.

Gillitzer, Christian and Peer Ebbesen Skov, "Evidence On Unclaimed Charitable Contributions From the Introduction of Third-Party Information Reporting in Denmark," Working Paper 2013.

Gronau, Reuben, "The Effect of Children on the Housewife's Value of Time," *The Journal of Political Economy*, 1973, pp. S168–S199.

Gruber, Jonathan and Botond Köszegi, "Is Addiction Rational? Theory and Evidence," *The Quarterly Journal of Economics*, 2001, *116* (4), 1261–1303.

Guyton, John L., John F. O'Hare, Michael P. Stavrianos, and Eric J. Toder, "Estimating the Compliance Cost of the US Individual Income Tax," *National Tax Journal*, 2003, pp. 673 –688.

Handel, Benjamin R, "Adverse selection and inertia in health insurance markets: When nudging hurts," *The American Economic Review*, 2013, *103* (7), 2643–2682.

Haque, Nadeem U and Se-Jik Kim, "" Human Capital Flight": Impact of Migration on Income and Growth," *Staff Papers-International Monetary Fund*, 1995, pp. 577–607.

Holt, Charles A and Susan K Laury, "Risk aversion and incentive effects," *American Economic Review*, 2002, *92* (5), 1644–1655.

Hoopes, Jeffrey L, Daniel H Reck, and Joel B Slemrod, "Taxpayer Search for Information: Implications for Rational Attention," *Forthcoming-American Economic Journal: Economic Policy*, 2014.

Inmar, "2013 Coupon Trends," Year End Report 2012.

Jones, Damon, "Inertia and Overwithholding: Explaining the Prevalence of Income Tax Refunds," *American Economic Journal: Economic Policy*, 2012, *4* (1), 158 –185.

Kaplow, Louis, "Accuracy, Complexity, and the Income Tax," *Journal of Law, Economics, and Organization*, 1998, *14* (1), 61–83.

Keys, Benjamin J, Devin G Pope, and Jaren C Pope, "Failure to refinance," Technical Report, National Bureau of Economic Research 2014.

Kleven, Henrik J and Mazhar Waseem, "Using notches to uncover optimization frictions and structural elasticities: Theory and evidence from Pakistan," *The Quarterly Journal of Economics*, 2013, *129*, 669–723.

Kleven, Henrik Jacobsen, Camille Landais, and Emmanuel Saez, "Taxation and International Migration of Superstars: Evidence from the European Football Market," *The American Economic Review*, 2013, *103* (5), 1892–1924.

_ , _ , _ , and Esben Schultz, "Migration and Wage Effects of Taxing Top Earners: Evidence from the Foreigners? Tax Scheme in Denmark," *The Quarterly Journal of Economics*, 2014, *129* (1), 333–378.

—, Martin B Knudsen, Claus Thustrup Kreiner, Søren Pedersen, and Emmanuel Saez, "Unwilling Or Unable to Cheat? Evidence From a Tax Audit Experiment In Denmark," *Econometrica*, 2011, pp. 651–692.

Koszegi, Botond and Matthew Rabin, "Mistakes in Choice-Based Welfare Analysis," *The American Economic Review*, May 2007, *97* (2), 477 – 481.

— and —, "Choices, Situations and Happiness," *Journal of Public Economics*, August 2008, *92* (89), 1821 – 1832.

— and —, "Revealed Mistakes and Revealed Preferences," in "The Foundations of Positive and Normative Economics: a Handbook" 2008, pp. 193 –209.

Kotakorpi, Kaisa and Jani-Petri Laamanen, "Complexity, Salience and Income Tax Filing Behavior: Evidence From a Natural Experiment," Manuscript, Working Paper, University of Turku 2013.

Laibson, David, "Golden Eggs and Hyperbolic Discounting," *The Quarterly Journal of Economics*, 1997, pp. 443–477.

Letzler, Robert and Joshua Tasoff, "Everyone Believes in Redemption: Overoptimism and Nudges," *Journal of Economic Behavior and Organization*, 2014, pp. 107–122.

Little, D Arthur D, "Little. Development of Methodology for Estimating the Taxpayer Paperwork Burden. Final Report to the Department of the Treasury, Internal Revenue Service," 1988.

Lucas, RE, "On the Mechanics of Economic Development," *Econmetric Society Monographs*, 1998, *29*, 61–70.

Madrian, Brigitte C and Dennis F Shea, "The Power of Suggestion: Inertia in 401 (k) Participation and Savings Behavior," *The Quarterly Journal of Economics*, 2001, *116* (4), 1149–1187.

Miller, Steven, Rosemary Marcuss, Susan Boehmer, Barry Johnson, and Wayne Kei, "Internal Revenue Service Data Book," Annual Report 2012.

Nelson, Forrest D, "Censored regression models with unobserved, stochastic censoring thresholds," *Journal of Econometrics*, 1977, *6* (3), 309–327.

Nichols, Donald, Eugene Smolensky, and T. Nicolaus Tideman, "Discrimination By Waiting Time In Merit Goods," *The American Economic Review*, 1971, pp. 312 –323.

O'Donoghue, Ted and Matthew Rabin, "Doing It Now Or Later," *American Economic Review*, 1999, pp. 103 –124.

_ and _ , "Incentives For Procrastinators," *Quarterly Journal of Economics*, 1999, pp. 769 –816.

_ and _ , "Choice and Procrastination," *Quarterly Journal of Economics*, 2001, pp. 121 –160.

_ and _ , "Procrastination On Long-Term Projects," *Journal of Economic Behavior & Organization*, 2008, *66* (2), 161 –175.

Piketty, Thomas, "Immigration et Justice Sociale," *Revue économique*, 1997, pp. 1291–1309.

Pitt, Mark M. and Joel Slemrod, "The Compliance Cost of Itemizing Deductions: Evidence from Individual Tax Returns," *The American Economic Review*, 1989, pp. 1224 –1232.

Redelmeier, Donald A and Christopher J Yarnell, "Road crash fatalities on US income tax days," *The Journal of the American Medical Association*, 2012, *307* (14), 1486–1488.

Rees-Jones, Alex, "Loss Aversion Motivates Tax Sheltering: Evidence From US Tax Returns," Working Paper 2013.

Saez, Emmanuel, "Do taxpayers bunch at kink points?," *American Economic Journal: Economic Policy*, 2010, pp. 180–212.

Shapiro, Jesse M, "Is there a daily discount rate? Evidence from the food stamp nutrition cycle," *Journal of Public Economics*, 2005, *89* (2), 303–325.

Silk, Tim and Chris Janiszewski, "Managing mail-in rebate promotions," Working Paper 2008.

Slemrod, Joel, "The return to tax simplification: An econometric analysis," *Public Finance Review*, 1989, *17* (1), 3–27.

_ and Christian Gillitzer, *Tax Systems*, MIT Press, 2013.

_ and Jon Bakija, "Taxing ourselves: a citizen's guide to the debate over taxes," *MIT Press Books*, 2008.

_ and Nikki Sorum, "The Compliance Cost of the US Individual Income Tax System," *National Tax Journal*, 1984, pp. 461 –474.

_ and _ , "The compliance cost of the US individual income tax system," *NBER*, 1985.

_ , Charles Christian, Rebecca London, and Jonathan A Parker, "April 15 syndrome," *Economic Inquiry*, 1997, *35* (4), 695–709.

Steuerle, Eugene, Richard McHugh, and Emil M Sunley, "Who Benefits from Income Averaging?," *National Tax Journal*, 1978, pp. 19–32.

Sydnor, Justin, "(Over) insuring modest risks," *American Economic Journal: Applied Economics*, 2010, *2* (4), 177–199.

Tazhitdinova, Alisa, "Optimal Reporting Threshold: Theory and Evidence From Charitable Contributions," Manuscript, University of California, Berkeley 2014.

_ , "Tax Breaks for Low Earners: Who Benefits From Them? Evidence from Mini-Jobs in Germany," *Working Paper*, 2015.

Wicks, John H, "Taxpayer compliance costs from the Montana personal income tax," *Montana Business Quarterly*, 1965, *3*, 36–42.

_ and Michael N Killworth, "Administrative and compliance costs of state and local taxes," *National Tax Journal*, 1967, pp. 309–315.

Yagan, Danny, "Moving to opportunity? Migratory insurance over the Great Recession," *Working Paper*, 2014.

Appendix A

How Taxing Is Tax Filing? Leaving Money on the Table Because of Hasle Costs.

A.1 Pitt and Slemrod (1989)

Pitt and Slemrod (1989) very elegantly apply the methods of Gronau (1973) and Nelson (1977) to assess the hassle cost of itemizing deductions by estimating a discrete choice censored model with unobserved censoring threshold.

To do so they estimate a cost and benefit function of itemizing deductions. The benefit of itemizing is given by $TS_i = X_i\beta + u_i$ where X_i are exogenous and observed characteristics, β is a vector of parameters and u_i an error term. Similarly, the cost of itemizing is assumed to be $C_i = Z_i\gamma + v_i$, where Z_i are exogenous and observed characteristics, γ a vector of parameters and v_i an error term. A person will itemize if $TS_i \geq C_i$. TS_i is only observed when $TS_i \geq C_i$ but C_i is never observed. Gronau (1973) and Nelson (1977) show that if u_i and v_i are uncorrelated or if there are some characteristics present in X_i but not in Z_i then the model is identified and a likelihood function can be maximized to estimate both TS_i and C_i. Pitt and Slemrod (1989) acknowledge that there is no reason to assume that the errors are uncorrelated but that there are some characteristics that are likely to be present in X_i but not in Z_i, therefore arguing that identification should be valid.

The set of exogenous and observable characteristics they consider to estimate both β and γ are whether a person is married, her AGI, the square of AGI, whether a person owns a farming business, the number of age exemptions a person claims and the number of exemptions claimed. The set of exogenous characteristics specific to β are positive investment income, the average state income and sales taxes for an income of \$40,000, the average property rate in a given state for an income of \$40,000 and an index of medical costs in a given state.

Given these exogenous and observed characteristics, they can estimate the cost and benefit function. They find that the average cost of itemizing is $106 (in 2014 dollars).

There is a deep connection between Pitt and Slemrod (1989) and my approach. By estimating a cost and benefit functions they are essentially estimating the amount of benefits forgone by taxpayers. This in turns translates into the missing mass I rely on. Essentially, they are estimating the missing mass of itemizers in the neighborhood of the standard deduction, which I am able to observe directly.

Their approach however relies on a series of assumptions both econometric assumptions necessary for identification and derived form Gronau (1973) and Nelson (1977) and the exogenous and observable characteristics they use to estimate the cost and benefit functions. My approach on the other hand relies on directly observing and non-parametrically assessing the magnitude of the missing mass in the neighborhood of the standard deduction.

There are two main issues with their approach. First, they are essentially using itemizers to estimate the cost of itemizing for taxpayers who fail to itemize. But there could be an intrinsic difference in the cost of itemizing for itemizers and non-itemizers. In particular, one of the reasons why taxpayers claim the standard deduction when they could benefit from itemizing is that they have systematically higher costs of filing taxes. In this case, Pitt and Slemrod (1989) would be underestimating the cost of itemizing for taxpayers who fail to itemize and therefore biasing their results downwards, explaining why they find a smaller cost.

Second, when Pitt and Slemrod (1989) estimate the cost and benefit function, they are constrained by choosing exogenous characteristics that are observable and are therefore likely to suffer from a missing variable bias. For example, the single largest deduction is the mortgage interest deduction. However they do not include house values nor mortgage interest rates in their estimation of the benefit. Income and property taxes are likely to be (imperfectly) correlated with a house value but will fail to capture any variation in interest rates. This is also true for the second and third largest deductions namely the state income and sales tax deduction and the property tax deduction. They cannot directly observe these variables, therefore they proxy for them using the average state income and sales tax and property tax for an income of $40,000. This is likely to introduce a bias in their estimation for any skewed distributions. Overall, the authors acknowledge - at least for the cost estimation - that "*The explanatory variables in the cost of itemizing equation were not as successful as in the tax saving equation.*" A biased estimate of the cost function - either due to the fact that itemizers have a lower cost than taxpayers who fail to itemize or to missing variables - would bias their estimates explaining the different magnitudes between our two estimates. My approach on the other hand does not rely on these strong assumptions as I can directly observe the missing mass of taxpayers who fail to itemize.

A.2 Sample Restrictions

Figure 1.1

The sample used for figure 1.1 are joint filers who itemize deductions. I focus on joint filers because they represent more than 50% of the population and the standard deduction is specific to the filing status. This means that I cannot show every tax filing status on the same graph because they would have different standard deductions. Joint filers provide the highest power because they have a larger sample size than of the other filing status. Figure A.6 shows the same patterns for single taxpayers.

Figures 1.2a, 1.2b and 1.4

In figure 1.2a and 1.4, I restrict attention to taxpayers who are married filing jointly for the reasons outlined in section A.2. In addition, in 1988 and 1989 there were two tax brackets (15% and 28%) and a tax rate "bubble" (33%). Most taxpayers who itemize deductions fall in the 28% marginal tax bracket. Therefore, to control for the effect of the marginal tax rate, I only consider taxpayers who fall in the 28% marginal tax rate bracket. This allows me to precisely calculate the amount of after tax forgone benefit.

In figure 1.2b, I focus on married filing jointly as well but I do not control for the marginal tax rate. This is because there are 25 different marginal tax brackets in 1970 ranging from 14% to 70%. Selecting taxpayers who have the same marginal tax rate will reduce the sample size too much rendering the estimates too imprecise.

Figure 1.7

In figure 1.7, I use the same sample restrictions as in figure 1.2a and 1.4 and break down the sample into deciles of income.

Figure 1.8

To generate figure 1.8, I consider joint filers as explained in section A.2. In figure (a), I consider all years from 1980 to 2006. In figure (b), I consider all years from 1998 to 2006 because few taxpayers used electronic filing prior to 2006.

Figure 2.1b

The variable indicating the week in which a return is processed by the IRS is only present in the SOI files in year 1980 to 1999. Thus, to generate figure 2.1b, I restrict attention to those years. I use the same sample restrictions as in figure A.2 in addition to dropping taxpayers who have a balance due to the IRS. If taxpayers owe money to the IRS, it is rational to wait as much as possible so as to save on interest.

Figure 1.9

To generate figure 1.9, I use the same sample restrictions as for figure 1.8 (a).

A.3 Taxpayers Who Have To Claim the Standard Deduction

In rare cases, taxpayers have to claim the standard deduction even when their itemized deductions exceed the standard deduction. This happens in the following four cases:

1. A married taxpayer whose spouse files separately and itemizes deduction.
2. In some states, a taxpayer who wants to itemize on her state tax return has to itemize on her federal tax return as well.
3. A taxpayer who is neither a citizen nor a permanent resident of the United States.
4. A taxpayer who can benefit from itemizing for alternative minimum tax purposes even though the standard deduction is greater than the sum of her itemized deductions.

A.4 Tax Reform Act of 1986 and Lagged Responses

Could there be any other exogenous variation altering the distribution of itemized deductions in 1989 affecting my main identification strategy? The majority of tax reforms happened following the TRA'86 and were enacted in 1987. Among those, there were some deduction reforms. Because I am comparing 1987 to 1989, I am implicitly controlling for the Tax Reform Act of 1986 (TRA'86) reforms. But there might be slow adjustments and lagged responses in 1988 or 1989. To rule these out, I consider all the reforms enacted by TRA'86 that could affect the level of deductions and show that it is reasonable to assume that the adjustment is immediate. Because all of the reforms reduced the amount of eligible deductions, they have no lagged response. To see this consider a hypothetical example: assume the charitable donation deduction is capped at $10,000. A taxpayer who was donating $15,000 will now only be able to deduct $10,000. Will the taxpayer reduce her donations? She might reduce them up to $10,000 but there is no reason to expect that she will reduce them any further. What does this imply for the level of deductions? We should observe a drop in deductions to $10,000 in 1987 and then *no further* drop in 1988 or 1989, ruling out any lagged responses. Since I am comparing 1987 to 1989, any reform that caps the amount of deductions should not affect my estimates. The deduction reforms enacted in 1987 are the following (source: IRS):

- Prior to 1987, medical deductions in excess of 5% of the AGI are deductible. In 1987, this threshold is increased to 7.5% of AGI, further limiting the allowable amount of medical deductions. There is no reason to assume that there will be a slow adjustment that spills over into 1988 or 1989 in this case.

- Sales taxes are not deductible anymore. For similar reasons, one should observe a drop in the total deductions in 1987 as sales taxes were a large portion of it but there should be no lagged effect.

- The home mortgage interest deduction is subject to a new limit. The home mortgage interest deductions for a given year are capped at the value of one's house (plus renovations). Anything in excess of the value of the house have to be deducted as personal interest for which only 65% of the total value can be deducted. First, the IRS estimated that very few taxpayers were affected by this reform since it is very rare that one's home mortgage interest in one given year exceeds the total value of one's house. Second, there is no reason to expect a drop in levels in the subsequent years. If a person is affected by this reform, in 1987 she will be forced to claim less deduction than she was previously claiming.

- Any interest for home mortgages in excess of 1 million dollars is not deductible anymore. Again, there is no reason to expect any lagged effects due to this reform because it caps the amount of deductions.

There are no other reforms affecting directly or indirectly the amount of itemized deductions an individual can qualify for.

A.5 Who Is More Likely to Switch to the Standard Deduction?

Identification Strategy

I use the panel dataset to identify the reasons taxpayers switch to the standard deduction. I focus on taxpayers who itemize deductions in year t and observe their decisions in year $t+1$. Therefore, the variable of interest is a dummy equal to 1 if the taxpayer switches to the standard deduction in year $t+1$ and 0 if she keeps itemizing. I drop individuals who have to file other Schedules (B, C, etc.) as they could bias the results.[1] I do not consider individuals who switch from claiming the standard deduction to itemizing because this decision is not as easily available as the opposite one. Indeed, a person with deductions in excess of the standard deduction threshold can easily decide between itemizing and not. But a person who is claiming the standard deduction is likely to have too few deductions in total to be able to itemize. All my results are clustered at the individual level.

[1]Some of these taxpayers have to deal with much higher record keeping costs than those required for itemizing.

I regress a variable that indicates that the individual is switching to the standard deduction on several variables of interest that I explain below. I also control for the level of deductions in year t, a polynomial of AGI, marital status, year and state fixed effects. The results are reported on table A.4. The regression specification is the following:

$$y_{it} = constant + newborn_{it} + newborn_{it} * close_{i(t-1)} + easyded_{i(t-1)} + ...$$

$$... + easyded_{i(t-1)} * close_{i(t-1)} + nopreparer_{i(t-1)} + nopreparer_{i(t-1)} * close_{i(t-1)} + x_{it} + \epsilon_{it}$$

- $y_{it} = 1$ if the taxpayer itemizes in year $t-1$ and switches to SD in year t and 0 if itemizes in year $t-1$ and year t.
- $close_{i(t-1)} = 1$ if the taxpayer reported itemized deductions within \$6,000[2] of the standard deduction in year $t-1$ and 0 otherwise.
- $newborn_{it} = 1$ if the taxpayer has a newborn in year t and 0 otherwise.
- $easyded_{i(t-1)} = 1$ if the sum of state tax and mortgage deductions in $t-1$ is greater than standard deduction and 0 otherwise.
- $nopreparer_{i(t-1)} = 1$ if the person does not use a tax preparer in year $t-1$ and 0 otherwise.
- x_{it} controls for a polynomial of income, the level of deductions in year $t-1$, the marital status, the state, the marginal tax rate and the year.

Newborn

Childbirth drastically reduces the amount of time available. Parents with a newborn are likely to value their time more than parents with no children because they have less leisure time available. For this reason, it is sensible to expect that families with newborns are more likely to switch to the standard deduction in the year when their child is born.

The results of the regression are reported in table A.4, column 1, 5 and 6. I find a significant and positive coefficient for the interaction term of being close to the standard deduction threshold and having a newborn. A taxpayer who is close to the standard deduction threshold and who has a newborn is 5% more likely to switch to the standard deduction.

An exogenous shock to the value of time such as child birth has significant effects over the decision to itemize providing additional evidence that taxpayers are trading off time and money when deciding to itemize.

[2] I choose \$6,000 because the pre and post-reform densities overlap 3 bins away from the standard deduction. I ran specifications with \$4000, \$5,000 and \$7,000 and found results of similar magnitude to the ones reported here.

High Ratio of Third Party Reported Deductions

The mortgage payment deduction and the state and local income tax deduction are both third-party reported implying that taxpayers receive a "statement" with the 1098 and W2 forms in January of year $t+1$, significantly reducing the record keeping cost.

The results of the regression are reported in table A.4 columns 2, 5 and 6. A taxpayer with a high proportion of mortgage interest and state tax deductions is 12% less likely to switch to the standard deduction when her deductions are close to the standard deduction threshold. This is consistent with the overall burden of tax filing being smaller for these two types of tax deductions because they have a relatively lower record keeping cost since both form W2 and form 1098 are received in January of year $t+1$, closer to the tax filing season. The fact that the record keeping cost is smaller if the receipts are sent closer to the tax filing season suggests that forms are harder to find or more likely to get lost as time elapses, possibly because they are not properly archived.

Tax Preparers

Tax preparers are readily available and provide taxpayers with assistance to file their returns. They also provide help in choosing the best options when filing taxes and ensuring that the taxpayer is "optimizing". However, they do not make the task of record keeping any easier.

Who uses tax preparers? Three types of individuals: low-income households who can get their refund faster when using tax preparers, households with complicated tax returns and households whose value of time is larger than the fee that they have to pay to the tax preparers.

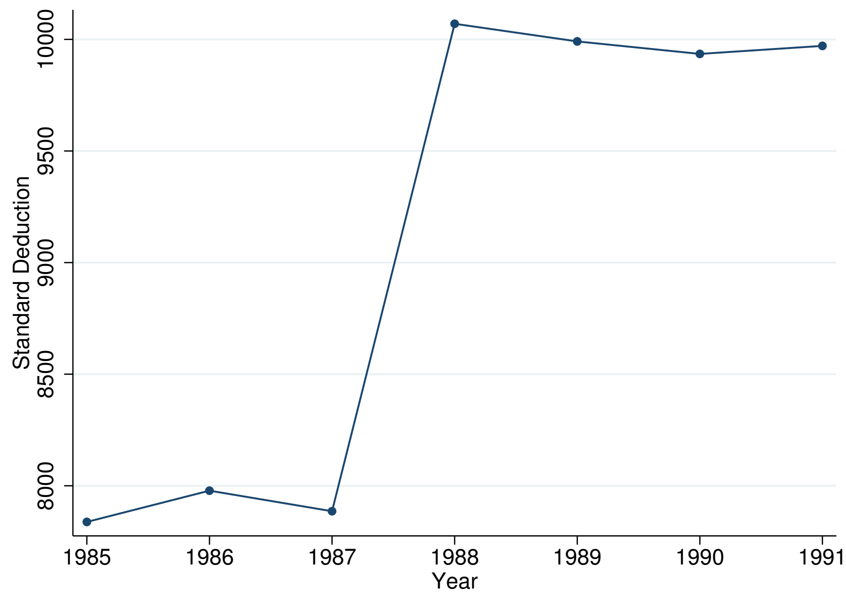
The taxpayers who itemize deductions are unlikely to have low-incomes simply because deductions are strongly correlated with income.

To control for individuals who are using tax preparers because of the complexity of their tax return, I drop any person who files any other schedules but Schedule A. Those include individuals who have capital gains or dividends, or individuals who have profit or losses from farming etc. These Schedules are significantly more complicated and a visit to tax preparers might be necessary even for the most tax-savvy taxpayers.

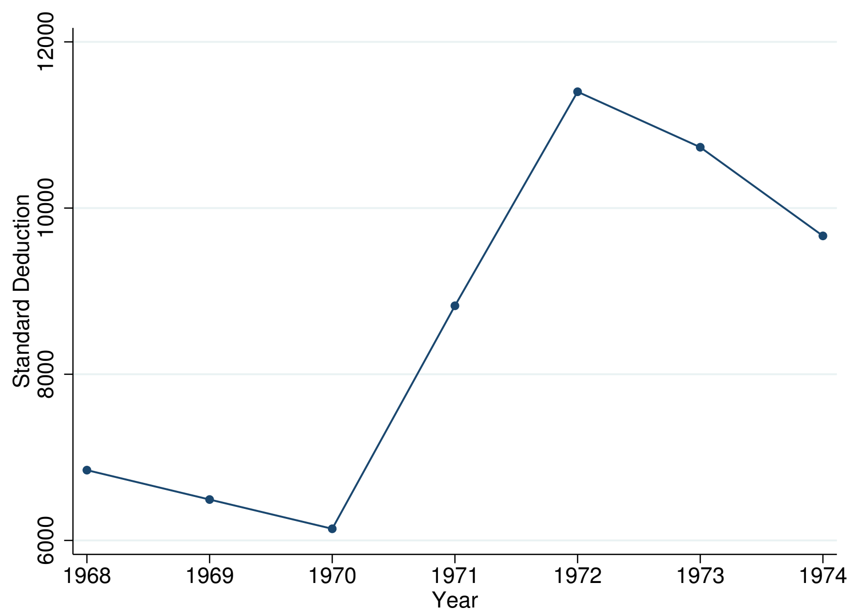
I find that using a tax preparer has no effect on the decision to itemize. The absence of effect is likely due to the fact that tax preparers cannot provide any assistance with record keeping which is more costly than filling out Schedule A.

Figure A.1: Reforms

(a) 1988 reform

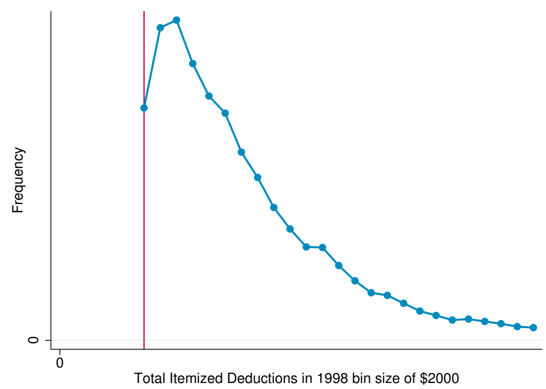


(b) 1971 reform

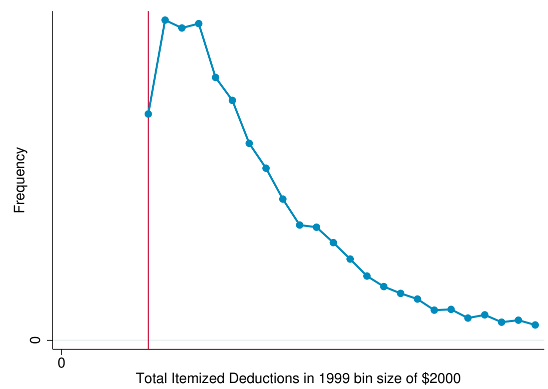


Notes: These graphs plot the level of the standard deduction by year. My identification strategy exploits the large increases in the standard deduction amount in 1988 and 1971. The amount of the standard deduction drops after 1972 because it is fixed in nominal terms. See appendix table A.1 for details.

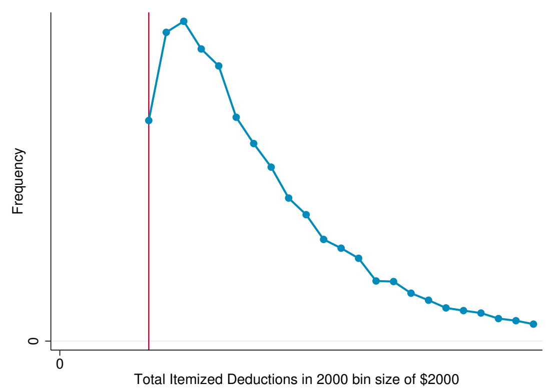
Figure A.2: Missing Mass In the Neighborhood of the Standard Deduction 1998-2003



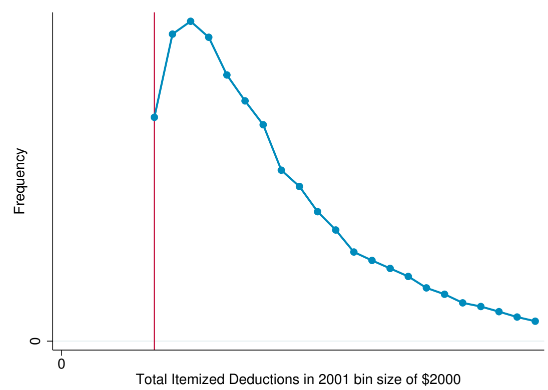
(a) 1998



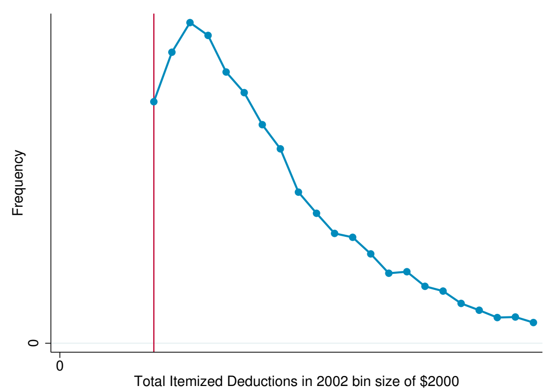
(b) 1999



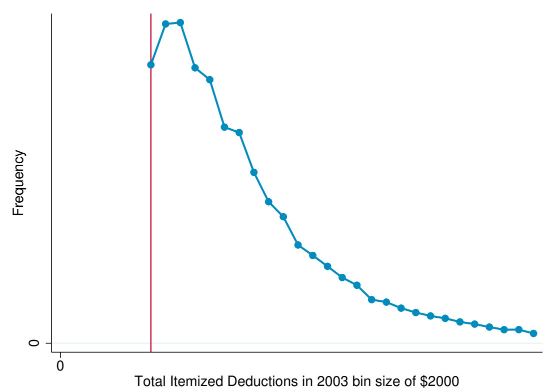
(c) 2000



(d) 2001



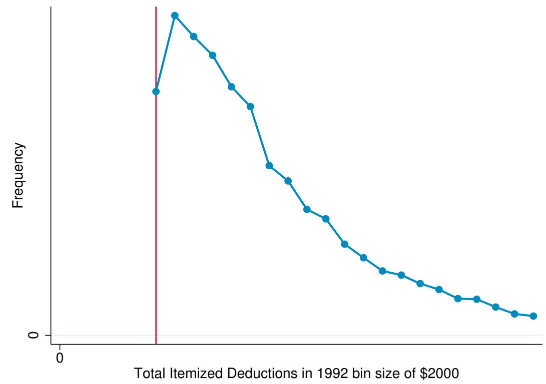
(e) 2002



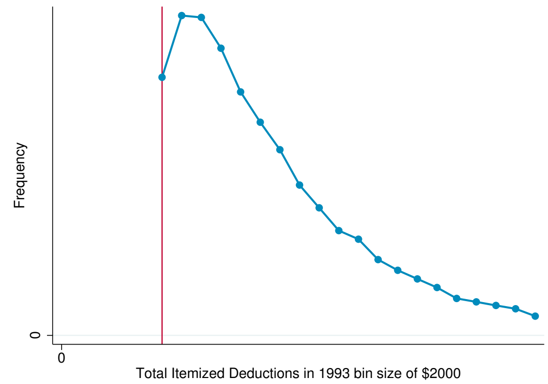
(f) 2003

Notes: The figures above plot the density of deductions for itemizers filing jointly. The bin size is \$2,000 and the vertical line represents the standard deduction threshold for each year. Notice the missing mass in the neighborhood of the standard deduction threshold.

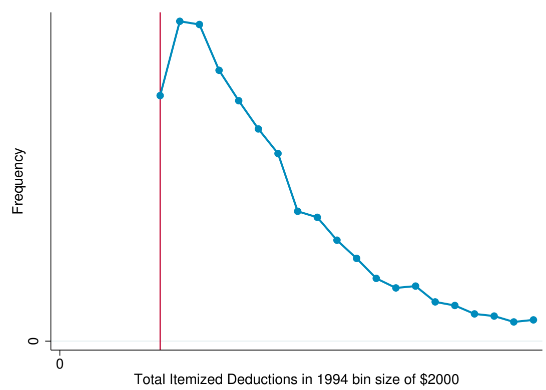
Figure A.3: Missing Mass In the Neighborhood of the Standard Deduction 1992-1997



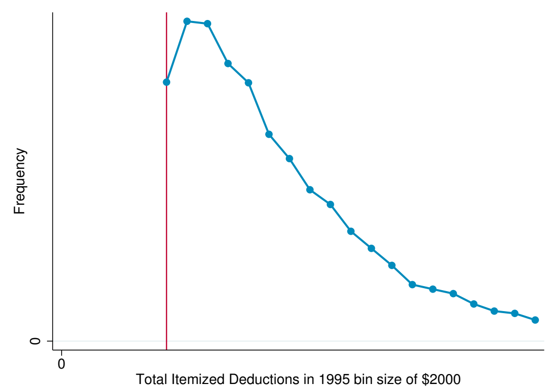
(a) 1992



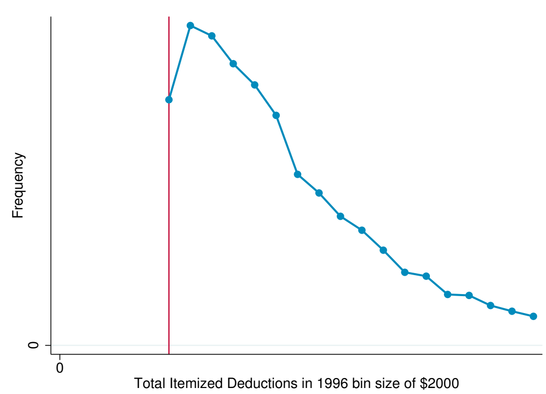
(b) 1993



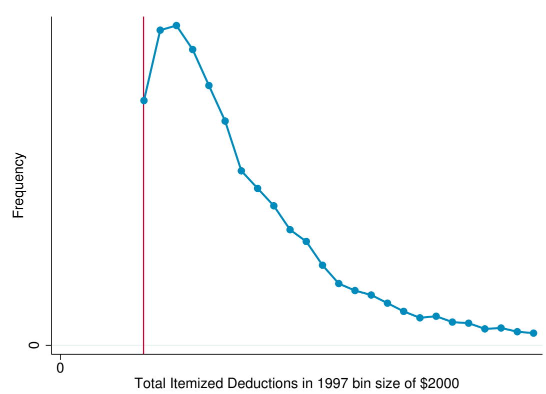
(c) 1994



(d) 1995



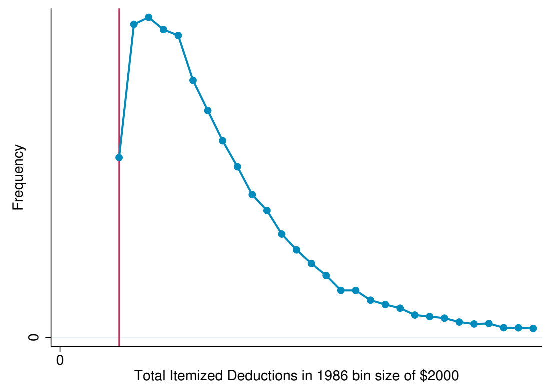
(e) 1996



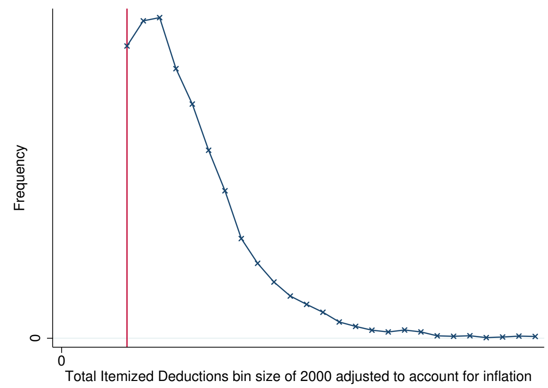
(f) 1997

Notes: The figures above plot the density of deductions for itemizers filing jointly. The bin size is $2,000 and the vertical line represents the standard deduction threshold for each year. Notice the missing mass in the neighborhood of the standard deduction threshold.

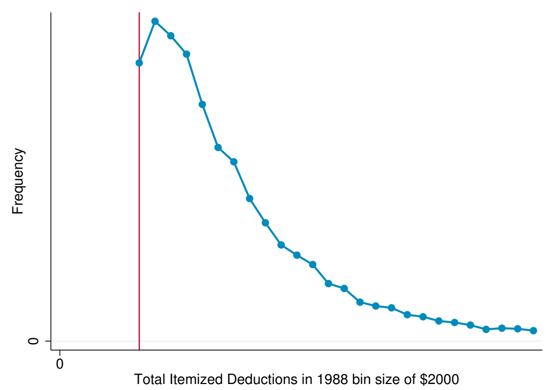
Figure A.4: Missing Mass In the Neighborhood of the Standard Deduction 1986-1991



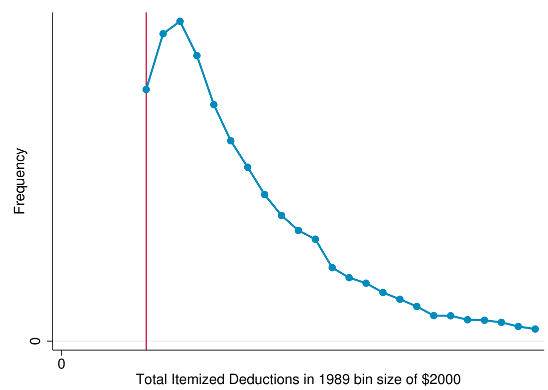
(a) 1986



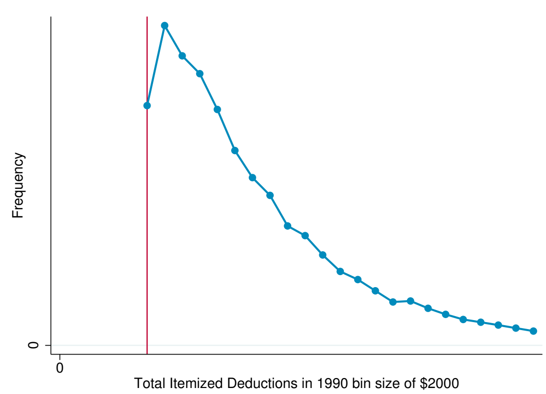
(b) 1987



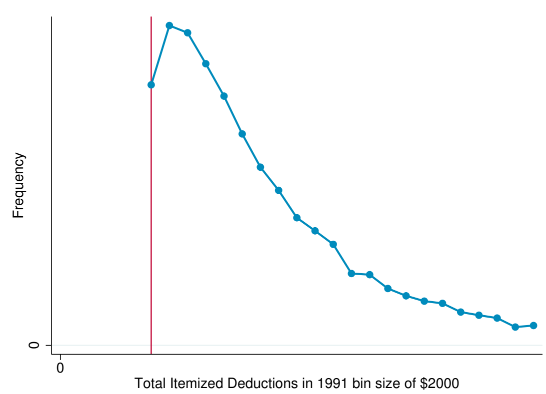
(c) 1988



(d) 1989



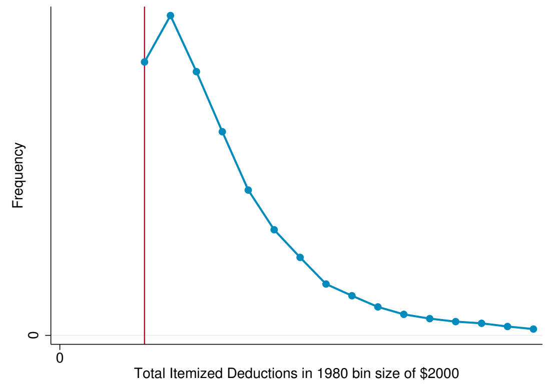
(e) 1990



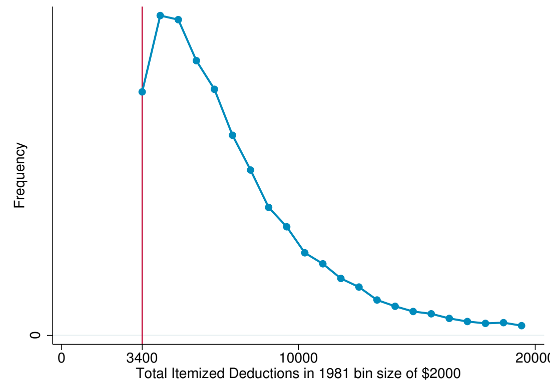
(f) 1991

Notes: The figures above plot the density of deductions for itemizers filing jointly. The bin size is \$2,000 and the vertical line represents the standard deduction threshold for each year. Notice the missing mass in the neighborhood of the standard deduction threshold.

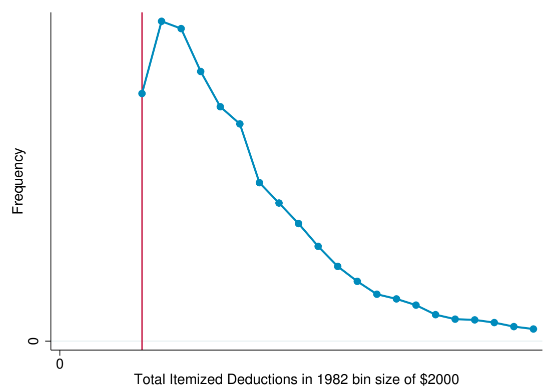
Figure A.5: Missing Mass In the Neighborhood of the Standard Deduction 1980-1985



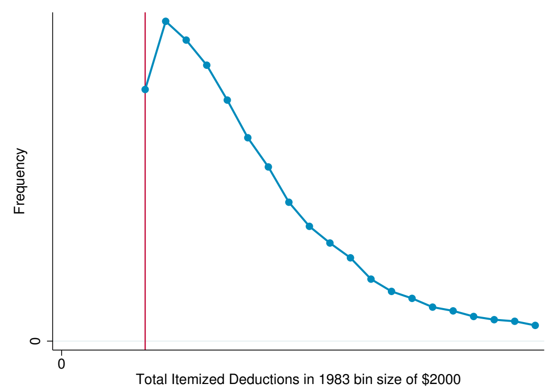
(a) 1980



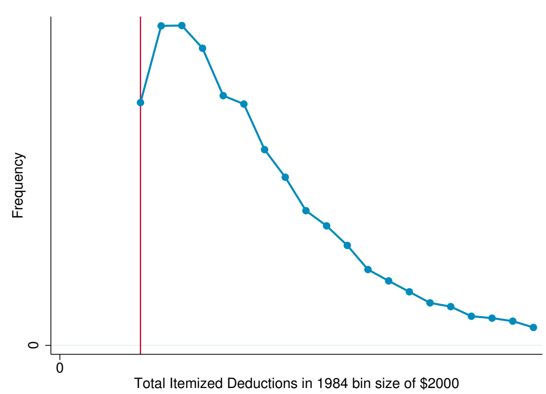
(b) 1981



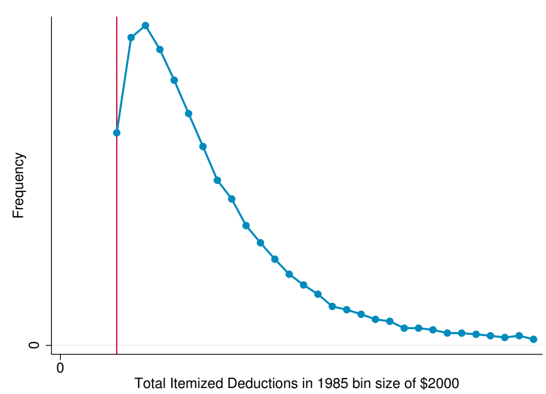
(c) 1982



(d) 1983



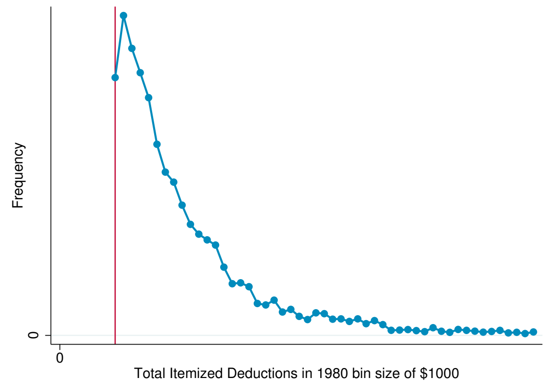
(e) 1984



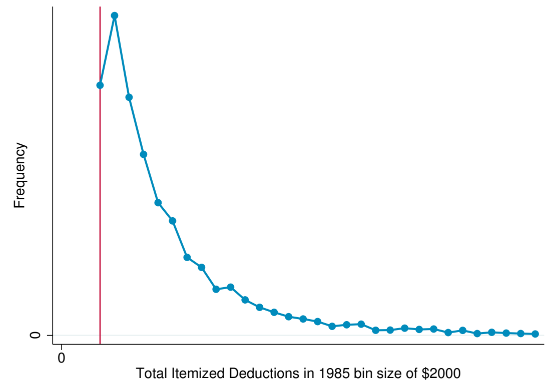
(f) 1985

Notes: The figures above plot the density of deductions for itemizers filing jointly. The bin size is \$2,000 and the vertical line represents the standard deduction threshold for each year. Notice the missing mass in the neighborhood of the standard deduction threshold.

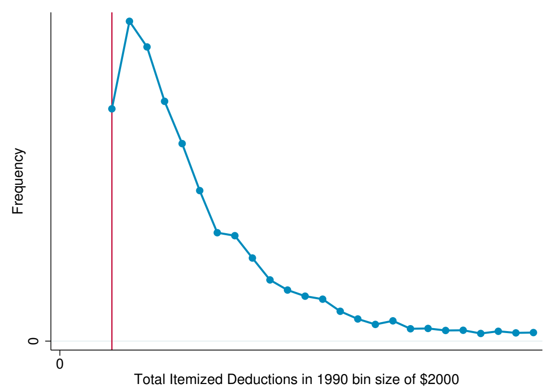
Figure A.6: Missing Mass In the Neighborhood of the Standard Deduction (Single Filers)



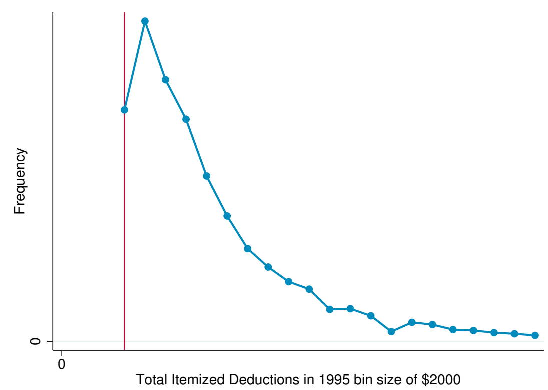
(a) 1980



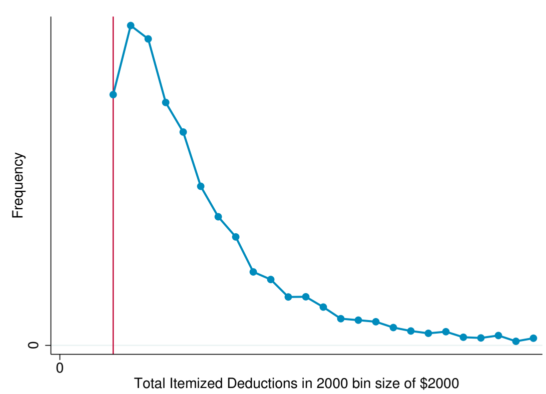
(b) 1985



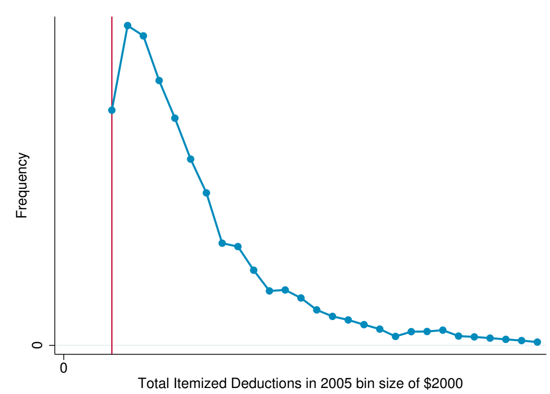
(c) 1990



(d) 1995



(e) 2000

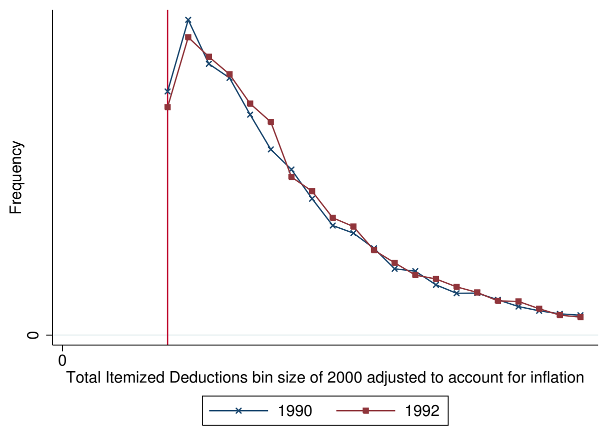


(f) 2005

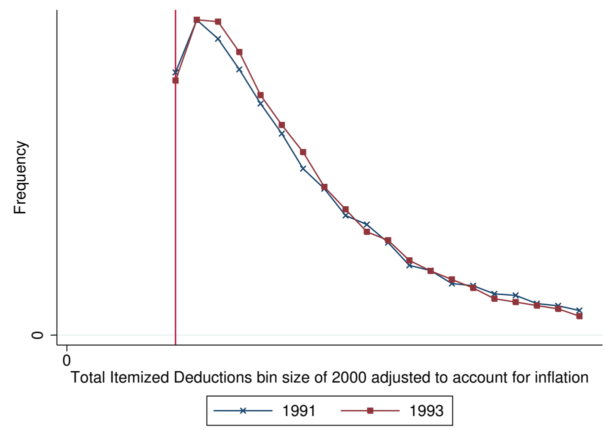
Notes:
The figures above plot the density of deductions for single filers who itemize deductions. The bin size is $2,000 and the vertical line represents the standard deduction threshold for each year. Notice the missing mass in the neighborhood of the standard deduction threshold.

Figure A.7: Placebo Test: Overlapping Densities In Years With No Reforms

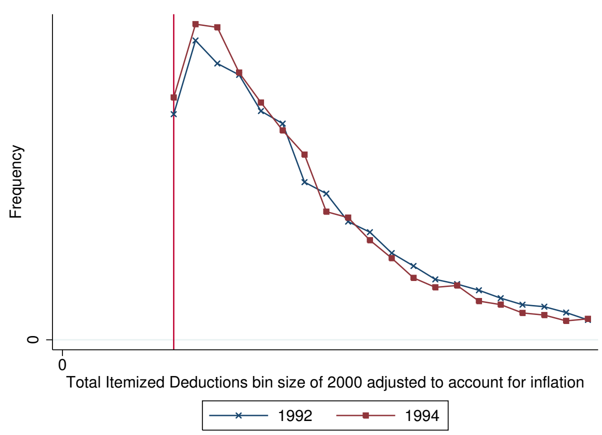
(a) 1990-1992



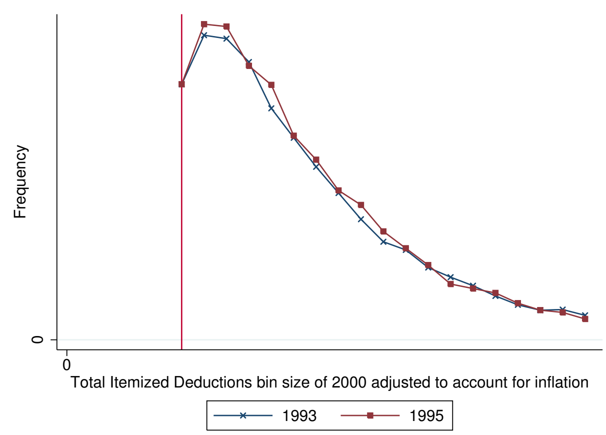
(b) 1991-1993



(c) 1992-1994

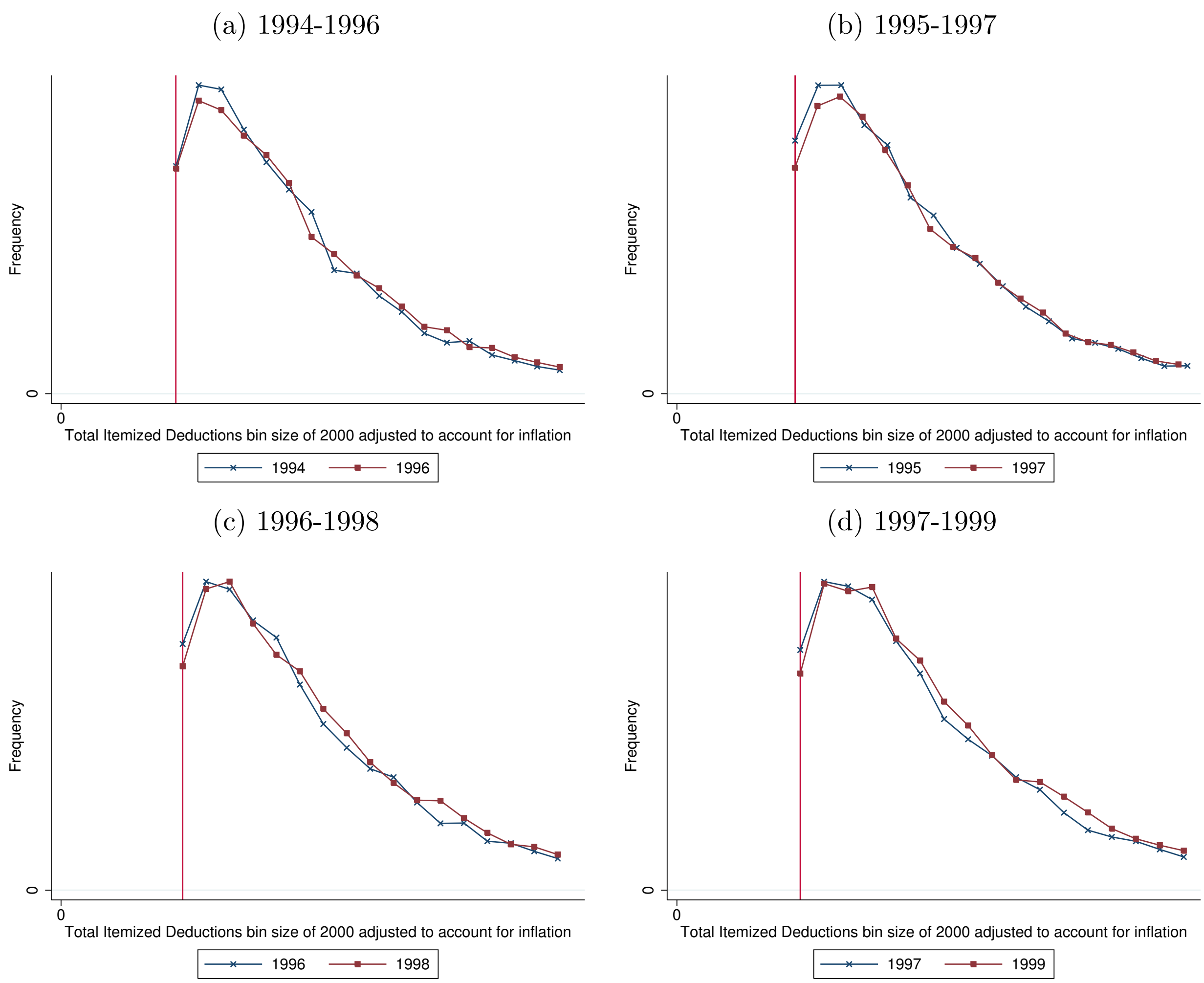


(d) 1993-1995



Notes: The figures above plot the density of deductions for itemizers filing jointly in years with no reforms of the standard deduction. Notice that there is no missing mass in the neighborhood of the standard deduction.

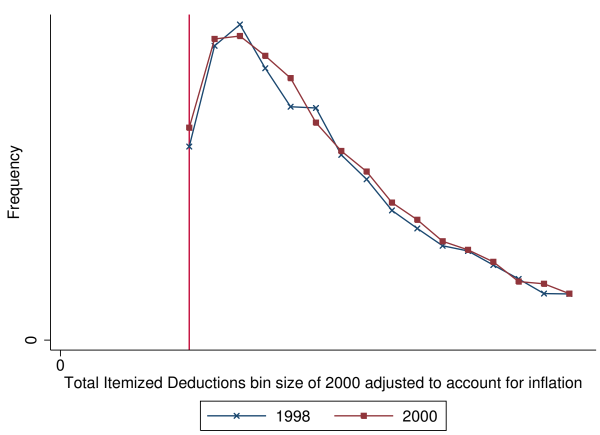
Figure A.8: Placebo Test: Overlapping Densities In Years With No Reforms



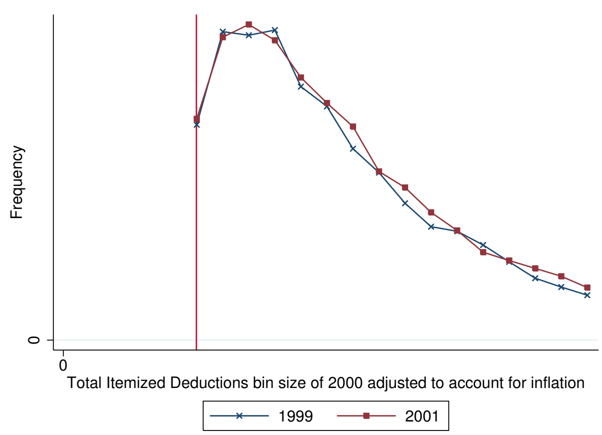
Notes: The figures above plot the density of deductions for itemizers filing jointly in years with no reforms of the standard deduction. Notice that there is no missing mass in the neighborhood of the standard deduction.

Figure A.9: Placebo Test: Overlapping Densities In Years With No Reforms

(a) 1998-2000



(b) 1999-2001



Notes: The figures above plot the density of deductions for itemizers filing jointly in years with no reforms of the standard deduction. Notice that there is no missing mass in the neighborhood of the standard deduction.

Table A.1: Standard Deduction By Year For Joint Filers

Year	Standard deduction	S.D. in 2014 $	Growth Rate	Year	Standard deduction	S.D. in 2014 $	Growth Rate
1961	1000	7968	0.00%	1984	3400	7796	0.00%
1962	1000	7889	0.00%	1985	3540	7838	4.12%
1963	1000	7786	0.00%	1986	3670	7978	3.67%
1964	1000	7686	0.00%	1987	3760	7886	2.45%
1965	1000	7564	0.00%	**1988**	**5000**	**10070**	**32.98%**
1966	1000	7353	0.00%	1989	5200	9991	4.00%
1967	1000	7133	0.00%	1990	5450	9935	4.81%
1968	1000	6846	0.00%	1991	5700	9971	4.59%
1969	1000	6492	0.00%	1992	6000	10189	5.26%
1970	1000	6140	0.00%	1993	6200	10223	3.33%
1971	**1500**	**8824**	**50.00%**	1994	6350	10208	2.42%
1972	2000	11400	33.33%	1995	6550	10240	3.15%
1973	2000	10732	0.00%	1996	6700	10174	2.29%
1974	2000	9665	0.00%	1997	6900	10243	2.99%
1975	2600	11514	0.30%	1998	7100	10378	2.90%
1976	2800	11724	0.08%	1999	7200	10293	1.41%
1977	3200	12580	0.14%	2000	7350	10169	2.08%
1978	3200	11693	0.00%	2001	7600	10515	3.40%
1979	3400	11158	0.06%	2002	7850	10560	3.29%
1980	3400	9831	0.00%	2003	9500	12301	21.02%
1981	3400	8911	0.00%	2004	9700	12234	2.11%
1982	3400	8394	0.00%	2005	10000	12199	3.09%
1983	3400	8133	0.00%	2006	10300	12173	3.00%

Notes: The table shows the standard deduction amounts from 1961 to 2006 for joint filers and its growth rate. The years that I use to identify the burden of itemizing deductions are in bold.

Table A.2: Standard Errors of the Difference Between the 1987 and 1989 Densities

Bin	Deduction Range	Difference	Standard Errors	z-stat
1	[9991, 11991]	0.00311***	0.00047	6.55
2	(11991, 13991]	0.00190***	0.00044	3.47
3	(13991, 15991]	0.00000	0.00040	0.02
4	(15991, 17991]	-0.00047	0.00041	-1.13
5	(17991, 19991]	0.00022	0.00038	0.59
6	(19991, 21991]	-0.00010	0.00033	-0.31
7	(21991, 23991]	-0.00041	0.00028	-1.45
8	(23991, 25991]	-0.00042	0.00025	-1.67
9	(25991, 27991]	-0.00032	0.00020	-1.60
10	(27991, 29991]	-0.00042**	0.00018	-2.24
11	(29991, 31991]	-0.00034**	0.00017	-2.00

Table A.3: Standard Errors of the Difference Between the 1970 and 1971 Densities

Bin	Deduction Range	Difference	Standard Errors	z-stat
1	[6140, 9140]	0.00373***	0.00102	3.64
2	(9140, 12140]	0.00288***	0.00090	3.20
3	(12140, 15140]	0.00307***	0.00074	4.11
4	(15140, 18140]	0.00083*	0.00046	1.81
5	(18140, 21140]	0.00019	0.00037	0.54
6	(21140, 24140]	0.00039	0.00027	1.45
7	(24140, 27140]	-0.00025	0.00018	-1.41
8	(27140, 30140]	-0.00001	0.00015	-0.09

Notes: These tables show the bootstrapped standard errors for the difference between bins in 1987 and 1989 and 1970 and 1971 for taxpayers with deductions below $30,000. Notice that only the first bins are statistically significantly different at the 99% level: the first two for the 1988 reform and the first three for the 1971 reform.
* denotes significance at the 10% level, ** at the 5% level and *** at the 1% level. I use 100 replications for the bootstrap estimation.

Table A.4: Determinants of the Likelihood of Switching to the Standard Deduction

Outcome:	Switch to the standard deduction: {0,1}					
	(1)	(2)	(3)	(4)	(5)	(6)
newborn x close to SD	0.03				0.05**	0.05**
	(0.02)				(0.02)	(0.02)
newborn	-0.02*				0.01	-0.01
	(0.01)				(0.01)	(0.01)
easy ded. x close to SD		-0.12***			-0.12***	-0.12***
		(0.01)			(0.01)	(0.01)
easy ded.		-0.12***			-0.18***	-0.11***
		(0.01)			(0.01)	(0.01)
no preparer x close to SD			-0.00		0.00	-0.00
			(0.01)		(0.01)	(0.01)
no preparer			-0.00		-0.01	0.00
			(0.01)		(0.01)	(0.01)
late x close to SD				0.04***	0.03**	0.04***
				(0.01)	(0.01)	(0.01)
late				0.02***	0.01	0.01
				(0.01)	(0.01)	(0.01)
close	0.06***	0.06***	0.06***	0.05***	0.10***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Controls	Yes	Yes	Yes	Yes	No	Yes
R^2	0.264	0.307	0.264	0.267	0.160	0.309
N	11799	11799	11799	11799	11799	11799
Clusters (individual)	4659	4659	4659	4659	4659	4659

Table A.5: Survey Based Estimates of the Hassle Costs of Taxation in the US

Article	Methodology	Aggregate Costs of Filing Taxes
Wicks (1965) and Wicks and Killworth (1967)	Survey of Montana residents	32% of state and 11.5% of federal tax revenue
Slemrod and Sorum (1985)	Survey of 2000 Minnesota residents	5% to 7% of total tax revenue
Arthur D Little (1988), Commissionned by IRS	Two separate surveys of 750 and 6200 taxpayers	1.59 billion hours
Slemrod (1989)	Estimate structural model based on survey of 2000 Minnesota residents	Not reported
Blumenthal and Slemrod (1992a)	Survey of 2000 Minnesota households in 1990	85 billion dollars
Guyton et al. (2003)	Survey and ITBM* simulations	18.7 billion hours dollars

Notes: This table reports the results of several research article documenting the cost of tax filing using survey evidence. *ITBM stands for the Individual Tax Burden Model.

Table A.6: Articles Documenting Low Take-Up Rates/Large Forgone Benefits

Article	Setting	Forgone Benefits
Steuerle et al. (1978)	Tax Benefits/Income Averaging	\$666
Blank and Card (1991)	Unemployment Insurance Benefits	Take up rate of less than 30% of eligible unemployed individuals
Madrian and Shea (2001)	Retirement Savings	50% match of retirement savings up to 6% of contributions
Sydnor (2010)	Home Insurance	Five times the insurance premium
Bhargava and Manoli (2011)	Taxes	Earned Income Tax Credit Benefits
Handel (2013)	Health Insurance	\$2,032 per year
Keys et al. (2014)	Mortgage Refinancing	Present discounted cost of \$11,500

Appendix B

Tax Filing Aversion or Procrastination?

B.1 Alternative Specifications of the Naive Present Bias Model

Increasing Marginal Disutility of Labor

In this section, I assume that the effort cost of itemizing is convex and show that it leads naive present-biased taxpayers to forgo large deductions because they fail to smooth effort over time. I assume that taxpayers have an increasing marginal disutility of labor: it is more painful to work on taxes after 4 hours of work than after one hour. Knowing that, the rational taxpayer smoothes effort of time: she files the 1040 form, state taxes and Schedule A on three separate days. The naive present-biased taxpayer procrastinates on filing her taxes and ends up "pulling an all-nighter" on the very last day experiencing more disutility than the rational taxpayer. Given that state taxes and the 1040 form are both compulsory she has no choice but to complete them. Itemizing however is optional and after working for several hours on her state taxes and 1040 form her marginal disutility of labor is so high that she is likely to turn down large sums of money to avoid spending more time looking for receipts and filling out Schedule A.

Assume the taxpayer needs to complete a task that requires H hours and provides a benefit b after it is completed. She can spread out the effort cost over T days. Her effort cost is given by a function $e(\cdot)$ with $e'(\cdot) > 0$ and $e''(\cdot) > 0$ implying that the effort cost increases in the number of hours spent working on taxes and the marginal disutility of effort is increasing.

The rational taxpayer will itemize provided that it is δ-worthwhile, and given that her marginal disutility of effort is increasing, she will smooth out the effort over the T days. Denote by h_i the number of hours spent working on taxes on day i. Formally, she is maximizing

$$\max_{h_1,h_2,\ldots,h_T} -\sum_{i=1}^{T} \delta^i e(h_i) + \delta^{T+1} b, \tag{B.1}$$

subject to

$$-\sum_{i=1}^{T} \delta^i e(h_i) + \delta^{T+1} b > 0, \tag{B.2}$$

and

$$-\sum_{i=1}^{T} h_i = H. \tag{B.3}$$

Since δ is a daily discount factor, I set it equal to 1.[1] Equation (B.2) ensures that itemizing is δ-worthwhile. The taxpayer will smooth effort over time by choosing $h_i = \frac{H}{T}$ for any period i, provided that condition (B.2) holds. The equilibrium path for the rational taxpayer is $(h_1^R, h_2^R, \ldots, h_T^R)$, such that for any i, $h_i^R = \frac{H}{T}$.

The naive-present-biased taxpayer has a preference for instant gratification that results in her discounting anything that happens on the next day by $\beta < 1$. Her naivete implies that she believes that in the next day she will not overvalue the present. This leads her to be time inconsistent. Formally, every period t she believes that she will smooth the effort cost over the remaining $T - t$ periods but fails to do so every day.

Because of her naivete, At time $t = 0$ she believes that she will be solving the following optimization problem:

$$\max_{h_1,h_2,\ldots,h_T} -\sum_{i=1}^{T} \delta^i e(h_i) + \delta^{T+1} b, \tag{B.4}$$

subject to

$$-\sum_{i=1}^{T} \delta^i e(h_i) + \delta^{T+1} b > 0, \tag{B.5}$$

and

$$-\sum_{i=1}^{T} h_i = H. \tag{B.6}$$

These conditions are the same as the one for the rational taxpayer: the naive taxpayer believes she will behave as if $\beta = 1$. But at time $t = 1$ she has a preference for instant gratification, and solves:

$$\max_{h_1,h_2,\ldots,h_N} -e(h_1) + \beta \left(-\sum_{i=2}^{N} \delta^i e(h_i) + \delta^{T+1} b \right), \tag{B.7}$$

[1]The main results are invariant to this assumption.

subject to

$$-\sum_{i=1}^{N}\delta^{i}e(h_i)+\delta^{T+1}b>0, \tag{B.8}$$

and

$$-\sum_{i=1}^{T}h_i=H. \tag{B.9}$$

Equation (B.7) is different from equation (B.1) in that everything except from period 1's cost is discounted by β.

Solving this problem in period t gives the following condition that describes the path of costs of the naive-present-biased taxpayer for $t<T$

$$e'(h_t)=\beta\sum_{i=t+1}^{T}\frac{1}{T-t}\delta^{i+1}e'\left(\frac{H-\sum_{i=1}^{t}h_i}{T-t}\right), \tag{B.10}$$

and for $t=T$

$$h_T=C-\sum_{i=1}^{T-1}h_i. \tag{B.11}$$

She equates the marginal disutility of effort today to the marginal disutility of effort in subsequent periods. She has wrong beliefs about β in the future and therefore thinks that she will smooth effort starting from tomorrow. Hence, for $i>t+1$, she believes that $h_i=\frac{H-\sum_{i=1}^{t}h_i}{T-t}$.

To calibrate this model, I assume that $\delta=1$ and $e(h)=\frac{h^{1+\sigma}}{1+\sigma}$. From equation (B.10) it follows that

$$h_t=\frac{\beta^{\frac{1}{\sigma}}(H-\sum_{i=1}^{t-1}h_i)}{T-t+\beta^{\frac{1}{\sigma}}} \tag{B.12}$$

I further assume that $\sigma=4$, $\beta=0.5$ and that taxpayers can start filing their taxes as early as February 1st and as late as April 15 (corresponds to $T=75$). In graph B.1(a), I plot the calibrated per-period disutility experienced by each type of taxpayer. In graph B.1(b), I plot the calibrated per-period number of hours spent working on taxes. The naive taxpayer works less than optimal the first days and works more the last days. This results in her experiencing a large disutility of effort in the last days because of the convexity of the effort function.

The taxpayer is required to file the 1040 form as well as any state income tax forms by April 15th. Itemizing however is optional. Given that she postpones most of her work to the very last days, itemizing can end up being very costly as her marginal disutility of effort in those days is high. It can become optimal at that time to forgo large amounts of deductions even if it only requires 5 hours of work given how large of a disutility it would imply. The rational taxpayer on the other hand smoothes effort over time resulting in a relatively low marginal disutility of effort and would not forgo the benefits of itemizing.

Idiosyncratic Shocks

In what follows, I assume that the cost of itemizing is stochastic: on some days, taxpayers have a high value of time (because they are busy) and on other days they are free and willing to itemize at a low cost. Rational taxpayers are aware of this variation in cost, have an option value of waiting and will do so to wait for a low cost realization. Naive present-biased taxpayers procrastinate on the task and fail to itemize even when costs are relatively low. This leads them to itemize on the last day exposing them to the full distribution of costs and leading them to forgo large benefits when cost realizations are high.

Assume the taxpayer has a choice between a costly task (itemizing deductions) and a cost-free task (claiming the standard deduction). Assume that the cost of itemizing in period t, is given by $C = (1+\alpha_t)c$ where c is the number of hours required to file Schedule A and α_t is stochastic and follows a distribution $F(\cdot)$. α_t represents the taxpayer's disutility from filing taxes on day t. Itemizing provides a deterministic benefit b. Claiming the standard deduction has a cost of zero and provides no benefit.

I build upon the search model developed by O'Donoghue and Rabin (1999b).[2]

Assume that the taxpayer has T periods to itemize. She is solving a Bellman equation with finite horizon. In the last period, she itemizes if $b - c(1+\alpha_T) > 0$, which happens with a probability $F(\frac{b}{c} - 1)$. Denote by γ_t^R the threshold for α below which the task is performed by the rational taxpayer in period t. Then $\gamma_T^R = \frac{b}{c} - 1$. The utility derived from itemizing is given by $V_T = F(\gamma_T^R)(b - c(1 + E(\alpha_T|\alpha_T < \gamma_T^R)))$.

In the period before, the task is performed when $b - c(1+\alpha_{T-1}) > V_T$ i.e. when the benefit today is greater than the expected benefit tomorrow. This means that the cutoff is given by $\gamma_{T-1}^R = \frac{b-V_T}{c} - 1$ and $V_{T-1} = F(\gamma_{T-1}^R)[b - c(1 + E(\alpha_{T-1}|\alpha_{T-1} < \gamma_{T-1}^R))] + [1 - F(\gamma_{T-1}^R)](V_T)$.

By induction, the cutoff and the continuation utility are given by:

$$\gamma_t^R = \frac{b - V_{t+1}}{c} - 1, \tag{B.13}$$

$$V_{t+1} = F(\gamma_{t+1}^R)[b - c(1 + E(\alpha_{t+1}|\alpha_{T-1} < \gamma_{t+1}^R))] + [1 - F(\gamma_{t+1}^R)](V_{t+2}). \tag{B.14}$$

The naive present-biased taxpayer discounts the future by $0 < \beta < 1$. She mistakenly believes she will behave similarly to the rational taxpayer in the subsequent periods and thinks her cutoff vector will be γ^r. Let's denote her true cutoff vector by γ^n and compute it backwards. In the last period, γ_T^n is given by $\beta b - c(1+\alpha_T) > 0$ i.e. $\gamma_T^n = \frac{\beta b}{c} - 1$. Notice that $\gamma_T^n < \gamma_T^r$. The naive present-biased taxpayer believes that she has the same cutoffs as the rational taxpayer, but her true cutoffs are given by $\gamma_t^n = \beta\gamma_t^R$. This implies that in every period, she is less likely to complete the task and more likely to delay it.

Denote by $Q(i, \beta, b)$ the probability that the taxpayer itemizes in a given period between $t = 1$ and $t = i$ given a present bias parameter β and benefit from itemizing b:

- $Q(1, \beta, b) = F(\beta\gamma_1^R)$,

[2] And more generally on Laibson (1997), O'Donoghue and Rabin (1999a), O'Donoghue and Rabin (2001) and O'Donoghue and Rabin (2008).

- $Q(2, \beta, b) = F(\beta\gamma_1^R) + (1 - F(\beta\gamma_1^R))F(\beta\gamma_2^R) = Q(1) + (1 - F(\beta\gamma_1^R))F(\beta\gamma_2^R)$,
- $Q(3, \beta, b) = F(\beta\gamma_1^R) + (1 - F(\beta\gamma_1^R))[F(\beta\gamma_2^R) + (1 - F(\beta\gamma_2^R))F(\beta\gamma_3^R)] = Q(2) + \prod_{i=1}^{2}[1 - F(\beta\gamma_i)]F(\beta\gamma_3)$,
- And by induction:

$$Q(t, \beta, b) = Q(t-1) + \prod_{i=1}^{t-1}[1 - F(\beta\gamma_i)]F(\beta\gamma_t). \tag{B.15}$$

$Q(T, \beta, b)$ is the probability that the task is completed at time T. Given the benefit that a taxpayer can derive from itemizing, her present-bias parameter etc. this model predicts the likelihood that she will itemize and can be matched to the estimates that I provided in the previous sections. $Q(T, \beta, b)$ decreases in β: as taxpayers are more present-biased the cutoff γ is decreased implying more delaying of the task. Once the deadline is reached, the naive present-biased taxpayers cannot delay filing anymore and face the full range of idiosyncratic cost realizations. Taxpayers who face a high cost realization will forgo large amounts of deductions.

B.2 Burden of Tax Filing When Taxpayers Are Naive Present-Biased

Time inconsistency implies a failure of the axiom of revealed preferences introducing a wedge between forgone benefits and hassle costs. In what follows, I estimate the hassle costs of taxation when taxpayers are naive present-biased. The estimated hassle costs under this model are smaller than when assuming that taxpayers are fully rational, because naive present-biased taxpayers forgo benefits both because of the cost of filing taxes and because of their bias. I use the Generalized Method of Moments (GMM) to estimate the model outlined in section B.1.

The counterfactual distribution that I reconstructed in section 1.3 allows me to calculate the proportion of taxpayers who claim the standard deduction when they could benefit from itemizing (table 1.1 and 1.2). I use these proportions to estimate the parameters of the model: the cost distribution $F(\cdot)$ and the bias for the present parameter β. I match equation B.15 that determines the probability of itemizing with the observed probabilities of itemizing in table 1.1 using the Generalized Method of Moments (GMM).

In section B.1, I assume that the cost is stochastic and follows a distribution $F(\cdot)$. To estimate the model, I assume that $F(\cdot)$ is the CDF of a uniform distribution with support $[0, \alpha]$ and that $T = 20$. I estimate α and β using GMM:

	β	$(1+\alpha)$
Rational	1	12.3
		(0.01)
Naive PB	0.35	7.00
	(0.01)	(0.21)

Notice that the estimated average hassle costs of the rational taxpayer are larger than that of the present-biased taxpayer. To explain such large forgone benefits and without assuming time inconsistency, one has to assume very large aversion to filing taxes. The naive present-bias model can explain the empirical findings without assuming high costs of filing taxes.

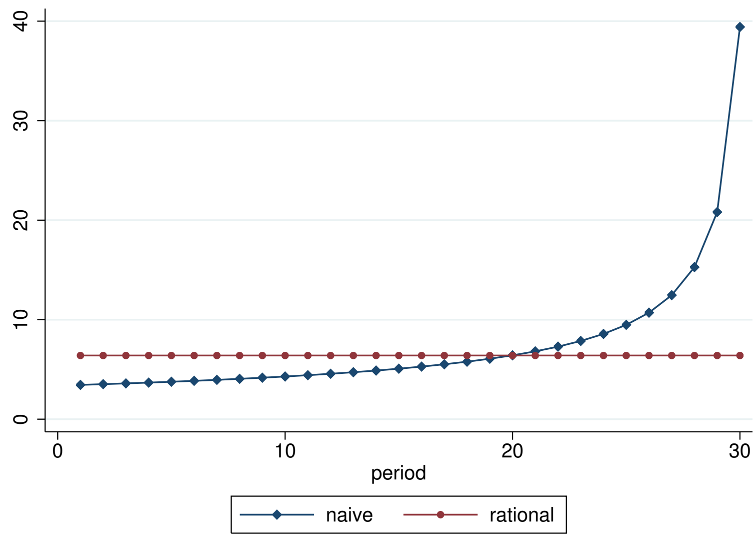
The difference between the estimated hassle costs when assuming full rationality and when assuming time inconsistency emphasizes the importance of accurate behavioral modeling when drawing welfare implications. If taxpayers are rational then the estimated cost distribution is the true cost of tax filing. On the other hand, if taxpayers are naive present-biased, then a portion of the burden of itemizing deductions is not due to hassle costs per se but due to the time inconsistency of taxpayers.

This is important in two ways. First, it draws different conclusions about the magnitude of hassle costs. Second, it calls for different policy interventions. If taxpayers are rational, then the only possible intervention is to reduce true hassle costs (less record keeping, less forms etc.). If they are time inconsistent, interventions that specifically target the bias itself should also be considered.

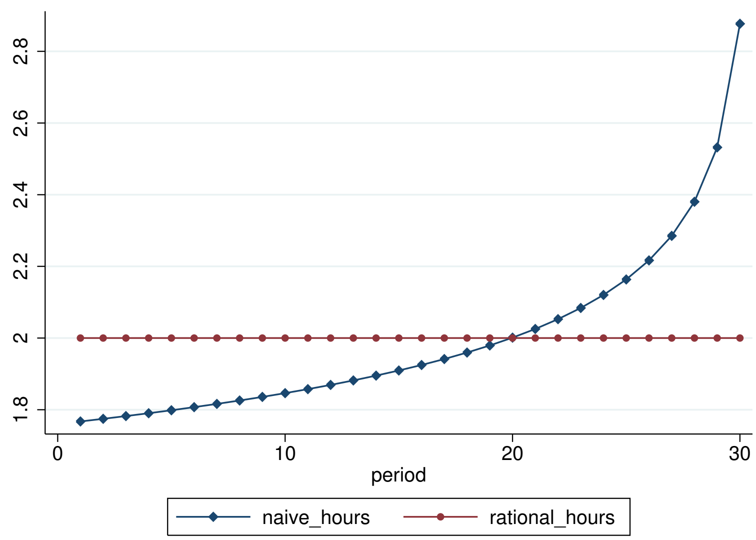
In table 2.2, I calculate the aggregate cost of filing taxes assuming taxpayers are naive present-biased using the parameters derived from the GMM estimation. The rational taxpayer has an upper bound on the cost distribution equal to 12.3 and the naive present-biased equal to 7. This means that assuming that taxpayers are rational implies 1.75 times larger hassle costs. This implies an aversion to tax filing coefficient of 2.23 for the naive present-biased individual. The cost of tax filing when the taxpayer is assumed to be naive present-biased amounts to 0.5% of GDP which corresponds to 84% of the aggregate hassle costs estimated when assuming that taxpayers are not time inconsistent.

Figure B.1: Calibration of Model With Convex Effort Costs

(a) Per-Period Disutility



(b) Per-Period Effort



Notes: These two graphs are the result of a calibration of the model outlined in section B.1. The first graph shows that the per-period disutility experienced by the naive present-biased taxpayer is higher than for the rational one. The second graph shows that the rational taxpayer smoothes effort over time whereas the naive present-biased one spends a lot of time filing taxes closer to the deadline.