How sensitive is the average taxpayer to changes in the tax-price of giving?

Peter G. Backus*

University of Manchester

and

Nicky L. Grant*

University of Manchester

Abstract

There is a substantial literature aiming to estimate the responsiveness of charitable donations to the tax incentive for giving in the United States. One approach has been to estimate the price elasticity of giving using tax return data of those who itemize their deductions, a group which is substantially wealthier than the average taxpayer. Survey data has also been used, yielding estimates of the price elasticity for the average taxpayer. The broad results from both arms of the literature present a counter-intuitive conclusion: the price elasticity of donations of the average taxpayer is larger than that of the average, wealthier, itemizer. We provide theoretical and empirical evidence that this conclusion results from a heretofore unrecognized downward bias in the estimator of the price elasticity of giving when non-itemizers are included in the estimation sample (generally with survey data). An intuitive modification to the standard model used in the literature is shown to yield a consistent and more efficient estimator of the price elasticity for the average tax payer under a testable restriction. We find strong empirical support for this restriction and estimate a bias in the price elasticity of about -1, suggesting the existing literature severely over-estimates the sensitivity of the average taxpayer. Our results suggest an inelastic price elasticity for the average taxpayer, where a statistically significant and elastic price response is found only for individuals in the top decile of income.

Keywords: Charitable giving, tax incentives, bias.

JEL Codes: D64, H21, H24, D12

*****: Backus: 2.004 Arthur Lewis Building, University of Manchester, Oxford Road, Manchester, M12FJ, UK (*email*: peter.backus@manchester.ac.uk); Grant: 2.007 Arthur Lewis Building, University of Manchester, Oxford Road, Manchester, M12FJ, UK (*email*: Nicky.grant@manchester.ac.uk). We are grateful for comments from seminar attendees at the University of Cape Town, University of Pretoria, University of Manchester, University of Barcelona, CREST, PEUK 2016 and the European Economic Association Conference 2017 as well as James Banks, Matias Cortes, Manasa Patnam and Jacopo Mazza. This paper was previously circulated under the title 'Consistent Estimation of the Tax-Price Elasticity of Charitable Giving with Survey data'.

1 Introduction

> *Some commentators have voiced the suspicion that, while a few sophisticated taxpayers (and their tax or financial advisors) might be sensitive to variations in tax rates, the average taxpayer is too oblivious or unresponsive to the marginal tax rate for anything like the economic model to be a realistic representation of reality.* Clotfelter (2002)

Tax incentives for charitable giving, particularly in the US, have received a great deal of attention from economists over the past several decades. In the US, taxpayers can deduct their charitable donations from their taxable income if they choose to itemize, or list, their deductible expenditures (e.g. donations, mortgage interest paid, state taxes paid) in their annual filing. Taxpayers can choose to subtract the sum of their itemized deductions or the standard deduction amount, whichever is greater, from their taxable income. The deductibility of donations produces a price (or tax-price) of giving equal to 1 minus the marginal tax rate faced by the donor if she itemizes and equal to 1 if not. This fact has been exploited in a sizable literature aimed at estimating the elasticity of charitable giving with respect to this price.

In this paper we revisit the estimation of the price elasticity of charitable donations. We provide theoretical and empirical evidence that the estimator obtained in the standard model using price variation arising from changes in itemization status (generally speaking, survey data) will be strongly downward biased. We show that controlling for itemization status yields a consistent, and more efficient estimator (relative to instrumental variable estimators) of the price elasticity under a simple, testable restriction which is strongly supported by the data. Using this model we find an inelastic price response of the average taxpayer, consistent with recent work in Hungerman and Wilhelm (2016). Only for those with income in the top decile do we find evidence of an elastic and statistically significant price response. This provides one explanation for the observation of Clotfelter (1985, 2002), and others (e.g. Aaron (1972)), that the estimated price responsiveness of charitable giving seems unrealistically large for the average taxpayer. Our findings are also significant for public policy analysis as a price elasticity less than unity is indicative that the tax deductibility of charitable donations may not be 'treasury efficient'.[1] Moreover, the optimal subsidies of giving derived in Saez (2004) depend heavily on the sensitivity of donors to the price of giving. For example, the optimal subsidy with a price elasticity of -1, which we reject for the average tax payer, is eight times larger than with a price elasticity of -0.5, which we cannot reject.

In general, estimates of the price elasticity of giving have been obtained using either tax-filer data (i.e. data from annual income tax forms) or from surveys. Using tax-filer data to estimate the price elasticity of giving limits the sample to those people who itemize their tax returns as no

[1] Tax deductibility of charitable donations is treasury efficient when the foregone tax revenue (and thus the decrease in the public provision of a public good) is exceeded by the increase in aggregate giving (the private provision of the public good). Conventionally, the threshold for efficiency has been a price elasticity of at least -1 (Feldstein, 1976). However, some have argued that the threshold ought to be larger (in absolute value) due to concerns about tax evasion (Slemrod, 1988), whilst others have argued that the deduction might be efficient even at price elasticities smaller than -1 (Roberts, 1984).

information on donations is recorded for non-itemizers.[2] But itemizers differ from non-itemizers in some important ways, most notably in their higher income.[3] As such, the estimated price elasticity obtained using tax-filer data is an estimate of the responsiveness of the average itemizer and may not reflect the responsiveness of the average, relatively poorer, taxpayer. Survey data, based on representative samples, provides an alternative source of information with which to estimate the price elasticity for the average taxpayer. In their meta-analysis, Peloza and Steel (2005) report that, on average, studies using tax-filer data (about 60 percent of the 69 studies they surveyed) estimate a price elasticity of −1.08 compared to a mean elasticity of -1.29 from studies using survey data, rejecting the null hypothesis that the mean responses are equal.[4] This suggests the economically rather counter-intuitive conclusion that the average taxpayer is more responsive to changes in the price of giving than tax-itemizers with higher average income.[5] Such a conclusion is in contrast to what has been found in the related literature looking at the elasticity of taxable income where higher income people have been found to be more sensitive to changes in tax rates (e.g. Feenberg and Poterba (1993), Moffitt and Wilhelm (2000) and see Saez, Slemrod and Giertz (2012) for an overview). Results in the current paper provide a simple explanation for the finding in the donations literature, namely that the price elasticity of donations estimated on survey data utilizing variation in itemization status suffer from a severe downward bias.

The literature in this area has long recognized two main sources of endogeneity in the price of giving. First, that the marginal tax rate is a function of taxable income, which, in turn, is a function of donations for itemizers (Auten, Sieg and Clotfelter, 2002). We follow a common practice in addressing this source of endogeneity (detailed below). Second, that the price of giving is a function of itemization status itself, and hence donations, for so-called 'endogenous itemizers' (Clotfelter, 1980), i.e. people that, conditional on their other deductible expenditures, are itemizers only because of the level of their donation. A common solution to this issue in the literature, using tax-filer data or survey data, has been to simply omit 'endogenous itemizers', generally a small share of the sample, leaving only exogenous itemizers with which to perform the estimation. In studies using tax-filer data this exclusion is sufficient to expunge the endogeneity from the price being a function of itemization status (e.g. Lankford and Wycoff, 1991; Randolph, 1995; Auten et al., 2002; Bakija and Heim, 2011), providing consistent estimation of the price elasticity of giving for the average itemizer.

However, if the interest is in consistently estimating the price elasticity of the average taxpayer then we must use samples including all kinds of taxpayers, including those who may not itemize their

[2] One exception to this rule is that between 1982 and 1986, non-itemizers could also deduct some or all of their donations.

[3] According to IRS records, the mean income of taxpayers who itemized their tax returns in 2013 was $147,938 compared to $48,050 for non-itemizers.

[4] In Batina and Toshihiro (2010), another survey of this literature, the mean price elasticity for tax-filer studies is -1.25 vs. -1.62 in studies using survey data. A similar pattern is found in Steinberg (1990) which surveys 24 early studies. More recently, Bakija and Heim (2011) find elasticities very close to -1 using a panel of tax filer data and both Yoruk (2010, 2013), Reinstein (2011), Brown et al. (2012) and Brown et al. (2015) generally find price elasticities in excess, sometimes substantially so, of -1 using the same survey panel data we use. In their working paper, Andreoni, Brown and Rischall (1999) use a Gallop survey of household giving and find price elasticities ranging from -1.73 to -3.35, magnitudes that they note are "consistent with the body of literature" (p. 11).

[5] We are not the first to find this disparity worthy of comment. Brown (1987) notes the same pattern but ultimately concludes that it is the failure to use Tobit estimators which can account for the larger elasticities obtained from survey data.

tax returns in certain periods and not in others. We show that in such samples a third, and heretofore unacknowledged, source of endogeneity remains even if 'endogenous itemizers' are excluded. This is because non-itemizers face a price equal to 1, and not the lower price of 1 minus the marginal tax rate as for itemisers, because their donations are sufficiently small (conditional on their other tax deductible expenses). In short, while itemizing is a function of donations for 'endogenous itemizers', so is *not* itemizing a function of donations for all non-itemizers. As a result, estimators of the price elasticity of giving based on data which includes non-itemizers (e.g. Brown and Lankford, 1992; Bradley, Holden and McClelland, 2005, Brown, Harris and Taylor, 2012; Yöruk, 2010, Yöruk, 2013; Brown, Greene, Harris and Taylor, 2015; Zampelli and Yen, 2017) will be downward biased.[6]

To understand the intuition of the price endogeneity arising from non-itemizers being included in the sample, consider the case when an agent switches from being an itemizer one year to a non-itemizer the next. Then, by definition her donations have decreased (holding her other deductible expenditure constant) and the price she faces has increased. The same argument holds in reverse for those who start itemizing. This difference between the mean donations of itemizers and non-itemizers cannot be picked up in a fixed effect for those who switch itemization status in some years. As such, a negative relationship will be found between the change in donations and the change in price, by construction; even in the extreme case where donation decisions are made at random. Below we prove this assertion formally, showing that the inclusion of non-itemisers, i.e. allowing those who switch status some periods, introduces a downward bias in to the estimator of the price elasticity.

A natural approach to address this bias would be to form a Two Stage Least Squares (2SLS) estimator, instrumenting for the change in price. We provide two exogenous instruments: the 'synthetic' and the actual change in marginal tax rates. Despite finding evidence that these instruments satisfy the identification condition, the variation in the price that they explain is small as in our setting most of the change in the price of giving comes from changes in itemization status. The 2SLS estimators then yield standard errors too large to make any economically meaningful inference.

Instead, we seek an alternative approach, noting that in this particular case the source of the endogenous price variation is measurable, i.e. itemization status or rather the change therein. We show formally that the Ordinary Least Squares (OLS) estimator of the price elasticity in a model which controls for change in itemization status removes this bias when the average change in price for those who stop and start itemizing are of the same magnitude, a testable restriction. We find with probability close to 1 that this restriction holds, suggesting this estimator is consistent. Moreover, since it exploits the maximal exogenous variation in the price and is estimated via OLS it is more efficient than any 2SLS estimator. In fact, we find the standard errors of the OLS estimator of the price elasticity in this model to be one-half, or less, of those obtained via 2SLS.

The paper proceeds as follows. Section 2 provides the formal theoretical results and discusses the bias in the standard model based on survey data. Section 3 discusses the data and our instruments, where Section 4 presents the empirical results. Finally, conclusions are drawn in Section 5. Proofs of

[6] Some of these studies do not exclude the endogenous itemizers (e.g. Brown and Lankford, 1992; Bradley, Holden and McClelland, 2005; Yöruk, 2010) meaning estimated price elasticities will suffer from both the known bias from endogenous itemizers and the bias outlined here from endogenous non-itemizers. Gruber (2004) and Reinstein (2011) impute itemization status, though such an approach can introduce nonclassical measurement error. In neither case, however, is the main aim of the study the consistent estimation of the price elasticity of giving.

the theoretical results along with extra empirical output are provided in an Appendix.

2 Estimating Price Elasticity of Donations

The standard empirical approach in estimating the price elasticity of donations has minimal theoretical underpinnings. Researchers have conventionally estimated donations as a linear function of price, income and various controls. The standard specification for a model of donations, introduced in the seminal work of Taussig (1967) and used in much of the literature since, is

$$\log(D_{it}) = \alpha_i + \beta \log(P_{it}) + \omega' X_{it} + e_{it} \tag{1}$$

$$P_{it} = 1 - I_{it}\tau_{it} \qquad I_{it} = 1(D_{it} + E_{it} > S_{it}) \tag{2}$$

where $D_{it} = D^*_{it} + 1$, D^*_{it} is the level of donations for household i at time t, $S_{it} = S^*_{it} + 1$, S^*_{it} is the standard deduction, E_{it} is all other tax deductible expenditure, τ_{it} is the marginal rate of income tax, P_{it} is the price of giving and β is the parameter of interest to be estimated, X_{it} is a vector of personal characteristics, including income and E_{it}, and ω is a corresponding vector of parameters, α_i is all time invariant unobserved heterogeneity and e_{it} is a random error term.[7] Here $I_{it} = 1$ if an agent itemizes, namely if the sum of deductible expenditures ($D_{it} + E_{it}$) is larger than the standard deduction (S_{it}).[8]

At any time t, people are either an *exogenous itemizer* ($I_{it} = 1$ where $E_{it} > S^*_{it}$), an *endogenous itemizer* ($I_{it} = 1$ where $D_{it} + E_{it} > S_{it}$ and $E_{it} \leq S^*_{it}$) or a *non-itemizer* ($I_{it} = 0$, i.e. $D_{it} + E_{it} \leq S_{it}$). As noted above, including endogenous itemizers in the estimation sample has long been recognized as causing the OLS estimator to be downward biased. A common solution to this issue in the literature has been to omit endogenous itemizers, generally a small share of the sample, leaving only non-itemizers and exogenous itemizers in the estimation sample.

This approach, however, only addresses one side of the problem as I_{it} is, in general, a function of D_{it}, not just for endogenous itemizers. A non-itemizer has donations bounded above (since $D_{it} \leq S_{it} - E_{it}$) and faces, by definition, a higher price than an itemizer, whose donations are unbounded. This is the converse to the bias caused by endogenous itemizers, who have donations bounded below ($S_{it} - E_{it} > 0$ and $D_{it} > S_{it} - E_{it}$) and face a lower price than non-itemizers (as the marginal tax rate is greater then zero). We show formally that even omitting endogenous itemizers, a large bias remains as a result of households itemizing in some years and not in others and that this bias is not expunged by the inclusion of individual fixed effects.

To show this issue we consider a model where endogenous itemizers are omitted (as is commonly

[7] As is conventional in the literature the level of donations is measured as a transformation of D^*_{it} which is strictly greater than zero so that $\log(D_{it})$ exists and is non-negative. Results in this paper are not sensitive to other positive transformations considered in the literature (e.g. inverse hyperbolic sine transformation or using D_{it}+10).

[8] Note that itemization status is not assigned, but rather people must choose to itemize themselves and some people may not itemize despite their deductible expenditure exceeding the standard deduction. One possible reason for this was found in Benzarti (2015) who shows that there is a cost of itemizing in terms of effort that amounts to about \$644 on average though with substantial heterogeneity around that figure. In this paper we use actual itemization status as reported by the surveyed household.

done in the literature) and individual effects (α_i) are removed via first differencing (FD).[9] We omit endogenous itemizers for simplicity and to maintain comparability with the results in the literature. First differencing equation (1) gives

$$\Delta \log(D_{it}) = \beta \Delta \log(P_{it}) + \omega' \Delta X_{it} + u_{it} \qquad \text{where} \quad u_{it} = \Delta \epsilon_{it} \tag{3}$$

There are three sources of price variation: 1) changes in taxable income and other observables which determine τ_{it} (which we control for), 2) the exogenous variation in the marginal tax rate schedule (which can be exploited to identify the price effect) and 3) changes in itemization status, I_{it}, which we show are endogenous. We define the following dynamic itemization behaviors for any i, t

I1 **Continuing itemizer:** $\Delta I_{it} = 0,\ I_{i,t-1} = 1,\ \ I_{it} = 1$
I2 **Stop itemizer:** $\Delta I_{it} = -1,\ I_{i,t-1} = 1,\ \ I_{it} = 0$
I3 **Start itemizer**: $\Delta I_{it} = 1,\ I_{i,t-1} = 0,\ \ I_{it} = 1$
I4 **Continuing Non-itemizer:** $\Delta I_{it} = 0,\ I_{i,t-1} = 0,\ \ I_{it} = 0$.

Note we refer to I2 and I3 collectively as 'switchers'. Define $V_{it} = S_{it} - E_{it}$ which is the standard deduction minus expenses plus one. So, $I_{it} = 0$ where $V_{it} \geq 1$ and $I_{it} = 1$ where $V_{it} < 1$. Table 1 summarizes the changes in price and the bounds on changes in donations (if any) for the four dynamic itemization behaviors (I1-I4).

Table 1: Changes in Donations and Price for I1-I4.

	$I_{it} = 1$	$I_{it} = 0$
$I_{i,t-1} = 1$	**I1** $\Delta\log(D_{it})$ is unbounded $\Delta \log(P_{it}) = \Delta \log(1 - \tau_{it})$	**I2** $\Delta \log(D_{it}) \leq \log(V_{it})$ $\Delta \log(P_{it}) = -\log(1 - \tau_{i,t-1})$
$I_{i,t-1} = 0$	**I3** $\Delta \log(D_{it}) \geq -\log(V_{i,t-1})$ $\Delta \log(P_{it}) = \log(1 - \tau_{it})$	**I4** $-\log(V_{i,t-1}) \leq \Delta \log(D_{it}) \leq \log(V_{it})$ $\Delta \log(P_{it}) = 0$

To show the bias we decompose the correlation between u_{it} and $\Delta \log(P_{it})$ into four component parts corresponding to each quadrant of Table 1. For continuing non-itemizers (bottom right quadrant) the change in price equals zero and hence does not introduce any bias. For continuing itemizers (top left) there is no bound on $\Delta \log(D_{it})$ and since u_{it} is exogenous and uncorrelated with $\Delta \log(1 - \tau_{it})$ no bias is introduced by this group either.

However, when $\Delta I_{it} = 1$ (stop itemizers, bottom left quadrant) then $\Delta \log(D_{it})$ (and hence u_{it}) are bounded below and $\Delta \log(P_{it}) < 0$, the two variables are negatively correlated. To see this more formally note that for start itemizers $I_{it} = 1$ (i.e $E_{it} \geq S^*_{it}$ as we consider only exogenous itemizers) and $I_{it} = 0$ (i.e. $D_{i,t-1} \leq S_{i,t-1} - E_{i,t-1}$), so donations in $t-1$ are bounded from above and donations in t are unbounded.[10] It then follows that $\Delta \log(D_{it})$ is bounded from below for start itemizers. Formally,

$$\Delta I_{it} = 1 \ \Rightarrow\ \Delta \log(D_{it}) \quad \geq \quad \log(D_{it}) - \log(S_{i,t-1} - E_{i,t-1}) \tag{4}$$

$$\geq \quad -\log(S_{i,t-1} - E_{i,t-1}) \tag{5}$$

[9] The FD estimator is used to simplify the exposition of the issue which will also occur more generally when using Within Group (WG) type estimators.
[10] Note that $S_{it} - E_{it} \geq 1$ when $I_{it} = 0$ since $D_{it} \leq S_{it} - E_{it}$ where $S_{it} = S^*_{it} + 1$ and $S^*_{it} \geq E_{it}$ by definition when $I_{it} = 1$ and $D_{it} \geq 1$ as $D_{it} = D^*_{it} + 1$.

where (5) follows since $\log(D_{it}) \geq 0$. Given that $\Delta\log(D_{it})$ is bounded below for start itemizers, the residuals, u_{it}, are also bounded below. Since u_{it} are mean zero (with the inclusion of a constant) the residuals are skewed to the positive for start itemizers; a group who also faces a decrease in price from 1 to $1-\tau_{it}$. The same argument holds in reverse for stop itemizers when $\Delta I_{it} = -1$ (top right quadrant) then $\Delta\log(D_{it})$ (and hence u_{it}) are bounded above and the distribution is skewed to negative values whereas the change in price is positive. Hence, changes in itemization status lead to a negative correlation between $\Delta\log(P_{it})$ and $\Delta\log(D_{it})$, even when $\beta = 0$. This negative correlation would emerge even if both donations and income (and thus τ_{it}) were randomly assigned.

Following the argument above, Theorem 1, derived formally in Appendix A, shows that the OLS-FD estimator of β in (3) is downward biased in the presence of switchers. For ease of exposition we assume $\omega = 0$ where $E[u_{it}] = 0$.[11] Equation (3) then collapses to

$$\Delta\log(D_{it}) = \beta\Delta\log(P_{it}) + u_{it} \tag{6}$$

and the OLS-FD estimator of β in (6) is $\hat{\beta}_{FD} = \frac{\sum_{i=1}^{N}\sum_{t=2}^{T}\Delta\log(D_{it})\Delta\log(P_{it})}{\sum_{i=1}^{N}\sum_{t=2}^{T}\Delta\log(P_{it})^2}$.[12]

To simplify the proof we assume that $(D_{it}, \tau_{it}, u_{it})'$ is i.i.d.[13] We also assume that τ_{it} conditional on income is strictly exogenous. Namely, while the marginal tax rate schedule itself is exogenous, τ_{it} will also be a non-linear function of taxable income. As such $\Delta\log(P_{it})$ is highly non-linear in income and if we fail to control for any potential non-linearity between $\Delta\log(D_{it})$ and $\Delta\log(Y_{it})$ then we introduce a correlation between $\Delta\log(P_{it})$ and u_{it}, violating the exogeneity condition. We check the robustness of our results to non-linear specifications in income, further details in Section 3.1.[14]

Define $p_1 = \mathcal{P}\{\Delta I_{it} = 1\}$, $p_{-1} = \mathcal{P}\{\Delta I_{it} = -1\}$, $\xi_1 = E[u_{it}\Delta\log(P_{it})|\Delta I_{it} = 1]$ and $\xi_{-1} = E[u_{it}\Delta\log(P_{it})|\Delta I_{it} = -1]$.

THEOREM 1 $\hat{\beta}_{FD} \xrightarrow{p} \beta + (p_1\xi_1 + p_{-1}\xi_{-1})/E[(\Delta\log(P_{it}))^2]$ where $\xi_1, \xi_{-1} < 0$.

Theorem 1 shows that is there a downward bias in the OLS-FD estimate of β when the probability of either stop or start itemizing is non-zero. In our sample p_1 and p_{-1} are approximately 0.1 and 0.08, respectively. The conditional covariance between u_{it} and $\Delta\log(P_{it})$ (ξ_1, ξ_{-1}) are negative for both forms of switchers.[15] Hence there is a downward bias in the estimator of β in the standard model where the intuition is made clear from Table 1 and the discussion above on the inherent endogeneity

[11] This assumption is made without loss of generality as we can make all the arguments below after partialling out X_{it} which we assume is exogenous. This method is used in the proof of Theorem 2 below.

[12] In practice a constant would be included in (6) so that the OLS-FD estimator would be demeaned ensuring $E[u_{it}] = 0$. All the arguments in the proof of Theorem 1 will go through unchanged on the variables de-meaned and this restriction is enforced for simplicity to clarify the exposition of the result.

[13] Extensions to non-i.i.d data hold straightforwardly utilising more general Weak Law of Large Number Results allowing quite flexible forms of heteroskedasticity and dependence.

[14] Theorem 1 can be generalized to much weaker assumptions on the correlation of u_{it} and τ_{it} though we wish to highlight even when τ_{it} is exogenous the change in price will not be as changes in itemization status are endogenous.

[15] We have omitted a constant here for simplicity but in the more general model including a constant all the relevant variables would be de-meaned.

in price from switching itemization status.[16]

The first thought towards a solution to the bias in Theorem 1 would be to search for an instrument for $\Delta\log(P_{it})$. An obvious choice is the exogenous change in the tax rate (conditioning on a given level of taxable income). Exogenous variation in marginal tax rates has been explicitly relied upon to estimate price elasticities of giving in the past (e.g. Feldstein, 1995; Bakija and Heim, 2011). This has been exploited as a largely undisputed source of exogenous price variation both in studies using survey and tax-filer data. We pursue an instrumental variable approach (discussed in detail below) and find evidence that the instruments satisfy the identification condition. Despite being identified, the correlation between our instruments and $\Delta\text{log}(P_{it})$ is small, as much of the variation in $\Delta\text{log}(P_{it})$ arises from variations in ΔI_{it}. As such the IV estimator is inefficient and yields standard errors far too large to forge any meaningful economic inference.

As such we seek a more efficient method to estimate the price elasticity. The source of the endogeneity in this problem is different to that classically found in many instrumental variable settings. Namely we know the source of endogenous variation in our regressor, $\Delta\log(P_{it})$, as it arises from changes in itemization status, which we can measure. Complications arise as $\Delta\log(P_{it})$ is a non-linear function of I_{it} and $I_{i,t-1}$. As such it is not immediately clear how to transform the standard model to expunge this endogenous variation in $\Delta\log(P_{it})$. Intuitively controlling for ΔI_{it} removes the variation in $\Delta\log(P_{it})$ from the change in itemization status and should (possibly under some restrictions) remove all the endogenous price variation in $\Delta\log(P_{it})$. This would then leave the maximal exogenous variation in price with which to consistently estimate β with more precision than the 2SLS-FD estimator.[17]

Theorem 2 below formalizes this intuitive argument, showing that controlling for change in itemization status removes the bias in Theorem 1 under a testable restriction that the average change in price for stop and start itemizers are of the same magnitude. We define the 'itemizer model', as opposed to the standard model of equation (3) which controls for ΔI_{it}, as

$$\Delta\log(D_{it}) = \gamma\Delta I_{it} + \beta\Delta\log(P_{it}) + \omega'\Delta X_{it} + e_{it}. \tag{7}$$

Define $z_{it} = (\Delta I_{it}, \Delta\log(P_{it}))'$ and $w_{it} = (z_{it}', X_{it}')'$ the OLS-FD estimator in the 'itemizer model'

$$\hat{\theta}_{FD}^{I} = \left(\sum_{i=1}^{N}\sum_{t=2}^{T} w_{it}w_{it}'\right)^{-1}\sum_{i=1}^{N}\sum_{t=2}^{T} w_{it}\Delta\log(D_{it}) \tag{8}$$

where we express $\hat{\theta}_{FD}^{I} = (\hat{\gamma}_{FD}^{I}, \hat{\beta}_{FD}^{I}, \hat{\omega}_{FD}^{I'})'$.

Intuitively the coefficient γ on ΔI_{it} allows the mean change in donations for switchers (conditional

[16] Note this problem as outlined here is unique to the US tax system though the literature on tax incentives for charitable giving extends to other countries. For example, Fack and Landais (2010) use data from France, Bonke, Massarrat-Mashhadi and Sielaff (2013) use data from Germany, Scharf and Smith (2010) use UK data. Each study contends with different issues surrounding the estimation of the price elasticity given the differently structured tax incentives for giving in each country. Our results here maybe of limited use in applications to similar studies in a different setting.

[17] Also though there is evidence the instrument is identified, the change in marginal tax rate is only mildly correlated with the change in log price. The Normal approximation of the 2SLS is known to be poorer the closer the instrument is to being unidentified, e.g Hansen, Heaton and Yaron (1996), Staiger and Stock (1997). As such a consistent OLS estimator utilizing the maximal amount of exogenous variation in $\Delta\log(P_{it})$ would be preferable to IV in this case, not just for efficiency and hence smaller standard errors but for more accurate inference.

on a given marginal tax rate and set of characteristics) to differ relative to non-switchers (by γ and $-\gamma$, respectively). In this sense this coefficient 'mops up' the bias derived in Theorem 1 by accommodating this mean shift in donations for switchers which is inherently correlated with the price causing a bias in estimates of β from equation (3).[18]

Further to note, γ in this case has no real economic interpretation but is a nuisance parameter which allows consistent estimation of β. We know even if donations were unresponsive to price, and indeed any other factors, it must be the case that $\gamma > 0$ as by definition the mean change in donations (conditional on other deductible expenses) is negative for stop itemizers, and vice-versa for start itemizers. It could be the case, however, that there is an 'itemization effect' (Boskin and Feldstein, 1977), namely the response to a price change from a change in I might differ to that of a corresponding price change from a change in τ. Alternatively, there may be a non-linear relationship between $\Delta \log(P_{it})$ and $\Delta \log(D_{it})$. In either case γ would partly pick up this price effect, and we may overstate the bias. This issue is discussed more in Section 4.1.[19]

Define $\bar{\tau}_1 = E[\log(1-\tau_{it})|\Delta I_{it} = 1]$, $\bar{\tau}_{-1} = E[\log(1-\tau_{i,t-1})|\Delta I_{it} = -1]$ and $C = \det(E[w_{it}w_{it}'])>0$ (ruling out any multi-collinear regressors in X_{it}).

THEOREM 2 If $E[e_{it}X_{it}] = 0$ (exogenous controls)

$$\hat{\beta}^I_{FD} \xrightarrow{p} \beta + \frac{p_1 p_{-1}}{C}(\bar{\tau}_1 - \bar{\tau}_{-1})(E[e_{it}|\Delta I_{it} = -1] + E[e_{it}|\Delta I_{it} = 1]). \tag{9}$$

By Theorem 2 (formally proven in Appendix A) there is no bias when either p_1 or p_{-1} are zero, which, as noted above, is not the case in our sample. More importantly it shows there is no asymptotic bias in $\hat{\beta}^I_{FD}$ if the average price increase for stop itemizers ($\bar{\tau}_{-1}$) is of the same magnitude as the average price decrease for start itemizers ($\bar{\tau}_1$). If (for a given ΔX_{it}) both stop and start itemizers have the same price elasticity (β) then the size of the endogenous response of $\Delta \log(D_{it})$ conditional on ΔX_{it} will be of equal magnitude (but opposite sign) provided they face the same magnitude of price change on average. This restriction ($\bar{\tau}_1 = \bar{\tau}_{-1}$) is testable and we find strong empirical support for the equality holding (discussed below). Moreover, if $\bar{\tau}_1 = \bar{\tau}_{-1}$ then Theorems 1 and 2 imply $\hat{\beta}_{FD} - \hat{\beta}^I_{FD}$ consistently estimates the bias in $\hat{\beta}_{FD}$ shown in Theorem 1.

3 Data, τ and instrumentation

We use data from the Panel Study of Income Dynamics (PSID) covering, bi-annually, 2000-2012. The PSID contains information on socio-economic household characteristics, with substantial detail on

[18] Note that we do not posit that the OLS-FD estimator in this auxiliary regression provides a consistent estimator of β by this argument alone. Equation (7) includes two endogenous variables, both $\Delta \log(P_{it})$ and ΔI_{it}, where we derive the bias in the estimate of β in this estimator in Theorem 2 below. We can show this bias is zero under an intuitive and testable restriction.

[19] If there is an itemization effect then the standard model is fundamentally misspecified, even aside from the bias in Theorem 1. To identify this itemization effect would prove problematic as we know γ would be a biased estimate of this itemization effect as it has to part reflect the mean differences in $\Delta \log(D_{it})$ arising purely from the definition of different types of itemizers. We consider the possibility of an itemization effect in the empirical analysis below.

income sources and amounts, certain types of expenditure, employment, household composition and residential location. In 2000, the PSID introduced the Center on Philanthropy Panel Study (COPPS) module which includes questions about charitable giving.[20]

We start with a raw sample with 58,993 observations.[21] Following Wilhelm (2006), we then drop the low income over-sample leaving us with a representative sample of American households. Households donating more than 50 percent of their taxable income, households with taxable income less than the standard deduction and households appearing only once during the observed period were dropped. These restrictions on the sample leave us with a working sample of 27,003 observations (5,845 households appearing in an average of 5.4 years). The unit of analysis is the household. All monetary figures are in 2014 prices.[22]

Actual itemization status (I_{it}) is reported in the survey. To identify the endogenous itemizers we compare the sum of deductible expenditures of each household (donations, property taxes paid, mortgage interest paid, state taxes paid, medical expenses in excess of 7.5 percent of gross income) to the standard deduction faced by the household (about \$6,000 for single people and \$12,000 for married couples, though it changes roughly in line with inflation each year).[23] Following convention, we define endogenous itemizers as those households who report itemizing and are predicted to itemize, but only when donations are included among the itemized deductions, i.e. $(0 < S - E < D)$. Endogenous itemizers make up 3 percent of the sample and 7 percent of itemizers. Exogenous itemizers $(E > S)$ make up 46 percent of the sample and 93 percent of the itemizers.[24]

The marginal tax rates with which we compute the price are obtained using the National Bureau of Economic Research's Taxsim program (Feenberg and Coutts, 1993). This allows for the calculation of rates and liabilities at both the state and federal level given a number of tax relevant household characteristics including earned income, passive income, various deductible expenditures, capital gains and marital status. As a result the calculated marginal tax rates are a function of the observable characteristics we submit to Taxsim and the exogenous federal and state tax codes.

We define the marginal tax rate as

$$\tau_{it} = \frac{\tau_{it}^{Fed} + \delta_{it}^{State}\tau_{it}^{State} - \tau_{it}^{State}\tau_{it}^{Fed}\delta_{it}^{Fed} - \tau_{it}^{State}\tau_{it}^{Fed}\delta_{it}^{State}}{1 - \tau_{it}^{State}\tau_{it}^{Fed}\delta_{it}^{Fed}} \tag{10}$$

where τ_{it}^{Fed} is the federal marginal income tax rate faced by household i in year t, τ_{it}^{State} is the state marginal income tax rate (42 states have a state income tax), δ_{it}^{S} is a dummy equal to one if donations can be deducted from state returns (3/4 of those states allow donations to be deducted), and δ_{it}^{F} is a

[20] Wilhelm (2006, 2007) contends that the data collected in the COPPS module are of better quality than most household giving survey data given the experience of the PSID staff.

[21] A significant topic of interest in this area has been the timing of donations and the responsiveness to permeant and transitory changes in the price (e.g. Randolph, 1995; Bakija and Heim, 2011). Due to the biannual nature of our data we do not consider this in our paper.

[22] Deflated using the Consumer Price Index: http://www.bls.gov/cpi/

[23] Self-reporting itemizers make up 48 percent of the sample. Our predicted itemization status gives an itemization rate of 53 percent and matches the declared itemization status in 78 percent of the cases. Our 'over-prediction' of itemization status is consistent with findings in Benzarti (2015) who shows that taxpayers systematically forego the savings they might accrue from itemizing in order to avoid the hassle of itemizing.

[24] There is a smaller share of the sample (6.5 percent) who report themselves as itemizers but for whom we fail to predict them as such. We include these households as exogenous itemizers. We have re-estimated all our models excluding them and results are qualitatively the same.

dummy equal to one if federal taxes can be deducted from state returns (allowed in six states) and I_{it} is equal to 1 if i itemizes in year t and 0 otherwise.

We construct three different versions of τ as defined in equation 10: τ^a, τ^b and τ^s. The marginal tax rate τ^a_{it} is calculated using i's tax relevant characteristics in t and i's actual level of giving in t. The related price of giving is then $P^a_{it} = 1 - I_{it}\tau^a_{it}$. However, as noted in Auten et al. (2002), τ^a_{it}, and thus P^a_{it}, will be endogenous, even for exogenous itemizers, as donations may be large enough to push i down to a lower tax bracket. To address this source of endogeneity, distinct from the source we focus on in this paper, we follow Auten et al. (2002) and Brown et al. (2012) in constructing an alternative marginal tax rate, τ^b, where τ^b_{it} is the mean of the marginal tax rate calculated by setting $i's$ giving in t to 0, sometimes called the 'first-dollar marginal tax rate in the literature, and the marginal tax rate calculated by setting i's giving in t at 1 percent of household income (the level used in Auten et al. (2002) and is about the median level of giving in our, as well as Auten et al.'s, data). The price variable we use in the regression analysis below is then $P^b_{it} = 1 - I_{it}\tau^b_{it}$ which, as Auten et al (2002) note, will be 'consistent' with the actual price of giving but will not suffer from the endogeneity from donations pushing a taxpayer to a lower tax bracket (the first source of endogeneity noted in the introduction). The correlation between P^a_{it} and P^b_{it} is 0.992.[25] We discuss τ^s in detail below

To help clarify the intuition of the bias derived in Theorem 1 we present descriptive statistics for changes in price and donations for the four types of dynamic itemization behaviors ($I1$ to $I4$ from Section 2) in Table 2. We present complete descriptive statistics for all other control variables in Appendix B.

Table 2: Descriptive Statistics of primary variables in first differences

	(1)		(2)	(3)	(4)
	Continuing itemizer ($I1$)		Continuing non-itemizer ($I2$)	Start itemizer ($I3$)	Stop itemizer ($I4$)
$\Delta\log P$	0.004		0.000	-0.246	0.252
	(0.091)		(0.000)	(0.099)	(0.100)
	$\Delta\log P \mid \Delta\log P > 0$	$\Delta\log P \mid \Delta\log P < 0$			
	0.070	-0.076			
	(0.073)	(0.074)			
$\Delta\log D$	0.042		0.002	0.579	-0.462
	(2.441)		(3.020)	(3.226)	(3.148)
	$\Delta\log D \mid \Delta\log P > 0$	$\Delta\log D \mid \Delta\log P < 0$			
	0.057	0.010			
	(2.445)	(2.456)			
Observations	3512	3002	7660	2195	1877

Notes: All monetary figures are in 2014 prices, deflated using the Consumer Price Index.

Price changes for continuing itemizers, coming from changes in marginal tax rates and taxable

[25] Some (e.g. Yöruk, 2010, 2013; Brown, et al., 2012; Brown et al., 2015) have used the price calculated using the first-dollar marginal tax rate as an instrument for P^a_{it} to address the endogeneity identified by Auten et al. (2002). Given the very high correlation between P^a_{it} and first-dollar price, 0.972 in our data, it is unsurprising that the use of the first-dollar price as an instrument or proxy is generally qualitatively unimportant to the results. It is important to note that such a 2SLS approach is valid in studies which exclude non-itemizers (e.g. Auten et al., 2002; Bakija and Heim, 2011) as the bias caused by switching itemization status (Theorem 1) is not present in the absence of switchers. However, the first-dollar price is not a valid instrument for P^a_{it} when switchers are in the sample under study as itemization status appears in the instrument making the instrument itself a function of donations.

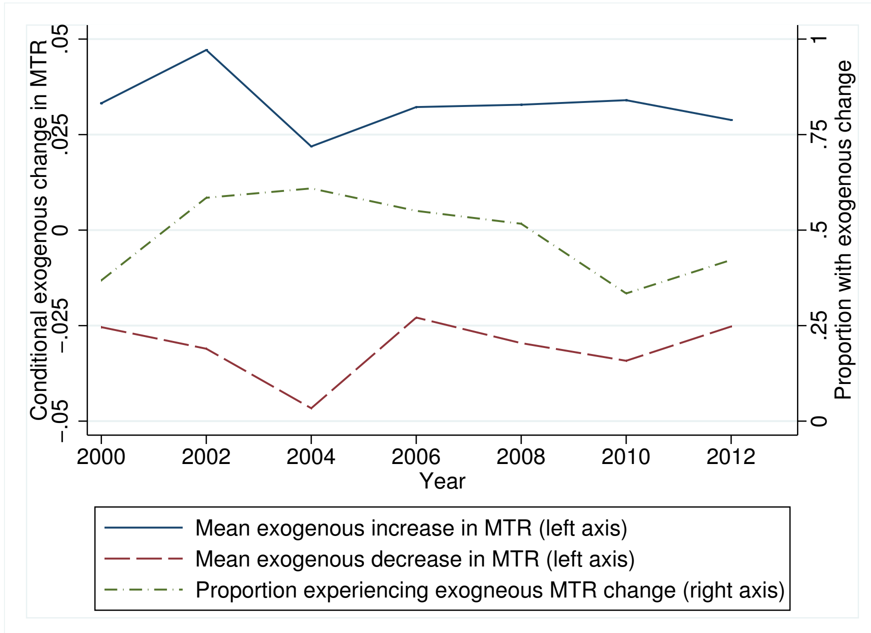
income (which we control for), are almost 0 on average. However, the mean increase in $\Delta \log P$ for continuing itemizers is 0.070 (median=0.043) and the mean decrease is -0.076 (median=0-.056). Start itemizers, for whom the price necessarily falls, see a 0.246 decrease in the log price. Stop itemizers (who necessarily face a price increase) see an average log price increase of 0.252. The price changes for start and stop itemizers are driven largely by the change in itemization status. Note that the price for continuing non-itemizers does not change, being equal to 1 by definition.

To compare the implied elasticities for continuing itemizers and switchers, we estimate the mean change in donations conditional on continuing itemizers facing an increase or decrease in the price. The mean increase in log donations, conditional on the continuing itemizer facing a price increase, is 0.057 and is statistically indistinguishable from the mean change in donations, conditional on the continuing itemizer facing a decrease, in price of 0.010 ($p-$value=0.461). The implied elasticity of donations for continuing itemizers is between 0.13 (indicating a positive price effect, albeit small, for those facing an decrease in price) and -0.81 (for those facing an increase in price). As we argue above, the mean change in donations for start and stop itemizers (conditional on deductible expenditures, which we control for) must be larger and smaller, respectively, than the changing donations for non-switchers. For switchers the implied elasticities are much larger (in absolute value) being -2.35 for start itemizers and -1.83 for stop itemizers. By Theorem 1 the negative bias in the standard model comes from the price variation from switchers. As such we would expect to find larger implied elasticities (in absolute value) from the switchers relative to the continuing itemizers, which is broadly consistent with these results.

Any attempt to identify the price elasticity of giving, via IV or otherwise, relies on exogenous variation to the tax code to introduce variation in the marginal tax rates and thus price. The largest changes to federal tax rates during our observed period occurred in the Economic Growth and Tax Relief Reconciliation Act of 2001 and the Jobs and Growth Tax Relief Reconciliation Act of 2003, which saw changes to the federal income tax brackets and marginal rates in those brackets. Other changes included adjustment of the manner in which dividends are taxed and changes to the Alternative Minimum Tax exemption levels (Tax Increase Prevention and Reconciliation Act of 2005) though Congress introduces a multitude of changes each year. In fact, the US Congress made nearly 5,000 changes to the federal tax code between 2001 and 2012 (Olson, 2012). Moreover, forty-three states impose some form of income tax and rates range from 0.36 percent in Iowa on income below $1539 up to 11 percent on income over $200,000 in Hawaii. As state income tax rates are set by state legislatures, the evolution of those rates over time differs from state to state providing temporal as well as cross-sectional exogenous variation in the state marginal income tax rates and thus the price. While it is indeed the case that the most significant changes to the federal tax code took place in the early 2000s, the exogenous variation is not isolated to that particular period.

To show this we construct a synthetic' marginal tax rate, τ_{it}^{s} in a manner analogous to τ_{it}^{b} but using i's tax relevant characteristics in t, including giving set to 0, but the tax code in place at $t-2$ (recall our data are biannual). Any difference between τ_{it}^{s} and τ_{it}^{b} is necessarily due to changes in the federal or state tax codes. Figure 1 plots the mean exogenous increases $\left(\overline{\tau_{it}^{b}-\tau_{it}^{s}}\middle|\, \tau_{it}^{b}-\tau_{it}^{s}>0\right)$ and decreases $\left(\overline{\tau_{it}^{b}-\tau_{it}^{s}}\middle|\, \tau_{it}^{b}-\tau_{it}^{s}<0\right)$ in marginal tax rates.

Figure 1: Mean exogenous increases and decreases in the marginal tax rates



Notes: The figure plots $\left(\overline{\tau^b_{it} - \tau^s_{it}}\middle| \tau^b_{it} - \tau^s_{it} > 0\right)$ and $\left(\overline{\tau^b_{it} - \tau^s_{it}}\middle| \tau^b_{it} - \tau^s_{it} < 0\right)$ on the left-hand axis and the proportion of the sample in each year experiencing an exogenous change in their marginal tax rate on the right-hand axis.

Between 40 and 60 percent of the sample experiences an exogenous change in the marginal tax rate they face. Over the observed period, 83 percent of households experience at least one exogenous change to their marginal tax while in the sample. Over the full period, the mean exogenous increase in a household's marginal tax rate was 0.033 (median=0.009) and the mean exogenous decrease in a household's marginal tax rate was -0.032 (median=-0.017).

To aid identification and overcome the bias derived in Theorem 1, we appeal to two instrumental variable approaches in addition to the estimator derived in Theorem 2. The first instrumental variable we use is the synthetic change in the marginal tax rate ($\tau^b_{it} - \tau^s_{it}$). This approach has been used in studies using tax-filer data (e.g. Fack and Landais, 2016). The correlation between $\tau^b_{it} - \tau^s_{it}$ and $\Delta \log P_{it}$ is, however, small (ρ=-0.067) as so much of the variation in $\Delta \log P_{it}$, about 70 percent, comes from changes in itemization status. The exogenous change in the marginal tax rates account for only about 1.7 percent of $\Delta \log P_{it}$.

Our second instrument is $\Delta\tau^b_{it}$ which is excludable under the assumption that $\Delta\tau^b_{it}$ is exogenous conditional on our set of controls, an implicit assumption frequently relied upon in the literature for identification. The correlation between $\Delta\tau^b_{it}$ and $\Delta \log P_{it}$ is 0.341 and about 10 percent of the variation in $\Delta \log P_{it}$ is explained by $\Delta\tau^b_{it}$.[26]

[26] A potential alternative is to use the price constructed with the 'synthetic' marginal tax rate as an an instrument for P^a_{it}. This approach has been used elsewhere in the literature seeking to study the effect of changes in marginal tax rates including work on charitable giving (e.g. Bakija and Heim, 2011; Fack and Landais, 2016). Note, however, that in our setting the itemization status, I_{it} would appear in any price, as defined in equation (2), used as an instrument meaning the synthetic change in the *price* would not be a valid instrument either.

4 Results

We present our primary results in Table 3. We estimate equation (3) including logged net taxable income, logged non-donation deductible expenditures (sum of mortgage interest, state taxes paid, medical expenditure and property tax paid plus $1)[27], logged age of the household head, the number of dependent children in the household as well as dummies for male household heads, being married, highest degree earned and home ownership. We also control for state and year fixed effects.

Note that conventionally models with a dependent variable distributed with a mass point at 0 might be treated as censored and thus require sophisticated econometric techniques (e.g. Tobits in McClelland and Kokoski (1994) and a double hurdle model in Huck and Rasul (2008)). However, such a mass point does not necessarily indicate censoring. In our case, it is not that we do not observe donations below a particular level but in fact the donation of zero is part of the choice set of the (non)-donor. Angrist and Pischke (2009) note that despite the convention, the use of non-linear models like Tobits when a bound is not indicative of censoring is not appropriate. We therefore use OLS to estimate the effect of changes in the price on the mean of the donations distribution including 0's.[28]

Table 3: Main results

	(1)	(2)	(3)	(4)
	Standard model	IV with $\tau^s_{it} - \tau^b_{it}$	IV with $\Delta\tau^b_{it}$	Itemizer model
$\Delta\log P^b$	-1.346***	-0.263	-0.168	-0.049
	(0.192)	(2.324)	(0.658)	(0.315)
Δitemizer				0.452***
				(0.095)
Observations	19342	19342	19342	19342
R^2	0.019	0.013	0.013	0.019
H_0 : IV estimator is identified		0.000	0.000	
$H_0 : \beta_{\Delta Logprice} \leq -1$	0.965	0.751	0.147	0.001

Notes: Results in column (1) are obtained from OLS-FD estimation of equation (3). Results in columns (2) and (3) are from 2SLS-FD estimation of equation (4) using $\tau^s_{it} - \tau^b_{it}$ and $\Delta\tau^b_{it}$ as the instrument, respectively. Results in column (4) are from OLS-FD estimation of equation (7). All standard errors are clustered (at the household level). The penultimate row shows the p-value from the first stage F-test. The tests reported in the last row is the one-sided t-tests of the estimated price elasticities being elastic (≤ -1) against the alternative hypothesis that the donations are price inelastic. Stars indicate statistical significance according to the following schedule: *** 1%, ** 5% and * 10%.

In column (1) we estimate the price elasticity of the average taxpayer using equation (3). We find an estimated elasticity of -1.35 (95 percent confidence interval: -1.72 to -0.97). These results are very much in line with those surveyed in Peloza and Steel (2005) and Batina and Toshihiro (2010) and with

[27] In general, non-donation itemizable expenditures (E) are not measured in survey data and even when information on E is available, as is the case with the PSID, it has not been, to our knowledge, included in models of donations in the literature to date. Such expenditures will be correlated with price via itemization status and likely correlated with donations since changes in, say, medical expenditures may likely affect one's donation decisions. As such omitting them will result in a biased estimator of the price elasticity. Including them, however, can be problematic as donations and non-donation deductible expenditures may be co-determined. We consider this issue further and check the robustness of our results to the exclusion of E as a control variable in Table 7 below

[28] We check the robustness of our results to the use of a Tobit estimator in Table 6 below.

more recent work using the same data we do (Brown, et al., 2012; Yöruk, 2010, 2013; Brown et al., 2015; Zampelli and Yen, 2017). We exclude endogenous itemizers and use a price constructed in line with Auten et al. (2002) to address the two long-recognized sources of endogeneity in τ. However, that the estimate in column (1) still suffers from the bias derived in Theorem 1 arising from the endogenous non-itemizers.

We re-estimate equation (3) using the full sample via 2SLS-FD. In column (2) we use the 'synthetic change in the marginal tax rate, $\left(\tau_{it}^b - \tau_{it}^s\right)$, as an instrument for $\Delta\log\left(P_{it}^b\right)$.

Though the correlation between $\left(\tau_{it}^b - \tau_{it}^s\right)$ and $\Delta\log\left(P_{it}^b\right)$ is small the instrument is well identified. The point estimate, -0.263, is much smaller (in absolute value) than that in column (1), though very imprecisely estimated (95 percent confidence interval: -4.82 to 4.29).

In column (3) we use $\Delta\tau_{it}^b$ as an instrument for $\Delta\log\left(P_{it}^b\right)$.[29] The point estimate is similar to that in column (2) and the standard errors are much smaller, though still too large to make meaningful economic inference (95 percent confidence interval: -1.45 to 1.21).

Though these estimates of β in columns (2) and (3) are derived from a consistent estimator, they both have large standard errors. Neither $\left(\tau_{it}^b - \tau_{it}^s\right)$ nor $\Delta\tau_{it}^b$ are particularly good instruments in our setting as so much of the variation in the price variable comes from itemization status. As such the t-tests of the null hypotheses that $\beta = 0$ and $\beta \leq -1$ have very low power. This make any meaningful economic inference difficult so there is little we can draw from these results.

In column (4) we estimate equation (7) via OLS-FD. As shown in Theorem 2 this specification will yield consistent estimates of β when $\bar{\tau}_1 - \bar{\tau}_{-1} = 0$. We can test this restriction, finding a sample estimate of $\bar{\tau}_1 - \bar{\tau}_{-1}$ of -0.0004 (p-value=0.862). The point estimate of the price elasticity in column (4), -0.05 (95 percent confidence interval: -0.67 to 0.57), is very close to and not significantly different from 0. There is strong evidence that the OLS-FD estimator in (4) is consistent and the standard errors fall by about half between columns (3) and (4). With this more precise estimator we find strong evidence to reject the null hypothesis that donations are price elastic, in contrast to the results from the 2SLS estimators which suffered from low power with which to test this hypothesis. We take this as evidence that the price response in the average taxpayer is not, in fact, elastic. Though the standard errors are much reduced in the itemizer model they remain quite large and so the question of whether the elasticity is closer to -1 or 0 remains open.[30]

As noted above, the consistency of the estimator relate to column (4) means that we can estimate the size of the bias in the estimates obtained from the standard model (column (1). Comparing these suggests the size of the bias is -1.30. This sizable bias, about the same size as the average estimated price elasticity from survey data, could explain why such strong price responses have been found in the literature using survey data.

4.1 Robustness checks

To test the robustness of our results to mis-specification we follow the good practice outlined in Athey and Imbens (2015) and re-estimate equations (3) and (7) while varying the data transformation,

[29] We also estimated columns (2) and (3) with higher order polynomials of each instrument, though no meaningful increases in precision were obtained in either case.

[30] A key drawback of the results based on the itemizer specification relative to the standard specification is that the variation in price is very small once we control for itemization status. The within-household variance of the exogenous change in price is only 0.004 when we control for itemization status compared to the within-household variance of 0.017 when we do not control for itemization status.

estimation sample, model specification and choice of estimator. First we consider our choice of transformation to eliminate the household fixed effects. In general we use first differencing to eliminate the household fixed effect, but we test the robustness of our result to within household mean differencing (WG) instead. We also test the sensitivity of our results to the exclusion of those households who never itemize during the observed period. We present results in Table 4

Table 4: Robustness checks I, WG and 'never itemizers'

	(1)	(2)	(3)	(4)
	Within Group		No never itemizers	
	Standard	Itemizer	Standard	Itemizer
$\Delta \log P$	-1.483***	-0.280	-1.342***	-0.013
	(0.169)	(0.283)	(0.167)	(0.347)
Δitemizer		0.427***		0.445***
		(0.086)		(0.107)
Observations	26282	26282	17882	17882
R^2	0.041	0.042	0.015	0.015
$H_0 : \beta_{\Delta \log P} \leq -1$	0.998	0.006	0.980	0.002

Notes: Results in columns (1) and (2) are obtained via OLS-WG estimation of equations (3) and (7), respectively. Results in columns (3) and (4) are obtained via OLS-FD estimation of equations (3) and (7), respectively, and excluding those households who never itemize during the observed period. All standard errors are clustered (at the household level). The test reported in the bottom row is the one-sided t-tests of the estimated price elasticities being elastic (≤-1) against the alternative hypothesis that the donations are price inelastic. Stars indicate statistical significance according to the following schedule: *** 1%, ** 5% and * 10%.

Results in columns (1) and (2) are obtained from OLS-WG estimation of equations (3) and (7) respectively. Results in columns (3) and (4) are obtained from OLS-FD estimation of equations (3) and (7), respectively, excluding those households who never itemize during the observed period and therefore experience no change in the price of giving. In both cases the pattern is the same: price elasticities in excess of -1 from the standard model and price elasticities close to and not different from 0, but different from -1, from the itemizer model.

We also test the robustness of the results to the inclusion of non-linear income effects in Table 5 by re-estimating equation (7) including quadratic (column (1)), cubics (column (2)), income decile group dummies (columns (3)) and, following Bakija and Heim (2011) decile groups interacted with years.

Table 5: Robustness checks II, allowing for a non-linear income effect

	(1)	(2)	(3)	(4)
	Quadratic income	Cubic income	Income decile groups	Income deciles $\times$Year
Δlog$P$	-0.037	-0.041	-0.039	-0.067
	(0.315)	(0.315)	(0.316)	(0.317)
Δitemizer	0.454***	0.453***	0.454***	0.449***
	(0.096)	(0.096)	(0.096)	(0.097)
Observations	19342	19342	19342	19342
R^2	0.021	0.021	0.021	0.018
$H_0 : \beta_{\Delta Logprice} < -1$	0.001	0.001	0.001	0.002

Notes: Results are obtained from OLS-FD estimation of equation (3). All standard errors are clustered (at the household level). The test reported in the bottom row is the one-sided t-tests of the estimated price elasticities being elastic ($\leq$-1) against the alternative hypothesis that the donations are price inelastic. Stars indicate statistical significance according to the following schedule: *** 1%, ** 5% and * 10%.

As seen in Table 5, the results do not qualitatively differ from our main finding in Table 3.

Next we see if the main findings are sensitive to the choice of estimator. Much of the previous literature using survey data has employed limited dependent variable estimator in light of the mass point at 0 donations (e.g. Reece, 1979; Lankford and Wycoff, 1991; Bonke et al., 2013). To produce results more directly comparable to the existing literature which uses Tobits and focuses on the effect of price on the conditional (on being positive) donations distribution we re-estimate our model using a correlated random effects (CRE) (Mundlak, 1978) Tobit estimator where the within household time means of each time varying regressor are included as additional regressors. Results are reported in Table 6.

Table 6: Robustness checks III, CRE Tobit estimation

	(1)	(2)	(3)	(4)
	Effect on E[log D]		Effect on E[log D|D>0]	
	Standard	Itemizer	Standard	Itemizer
Δlog$P$	-1.313***	0.025	-1.029***	0.020
	(0.218)	(0.387)	(0.171)	(0.306)
Δitemizer		0.484***		0.382***
		(0.117)		(0.092)
Observations	26282	26282	26282	26282
Pseudo-R^2	0.075	0.079	0.075	0.079
$H_0 : \beta_{\Delta \log P} \leq -1$	0.851	0.002	0.864	0.001

Notes: Results obtained from CRE Tobit estimation. All standard errors are clustered (at the household level). The test reported in the bottom row is the one-sided t-tests of the estimated price elasticities being elastic ($\leq$-1) against the alternative hypothesis that the donations are price inelastic. Stars indicate statistical significance according to the following schedule: *** 1%, ** 5% and * 10%.

We report the estimated effects on the unconditional mean of log donations in columns (1), for the standard specification, and in column (2) for the itemizer specification. These are comparable to the results in columns (1) and (4), respectively, in Table 3. We report the effects on the conditional mean donation, conditional on donations being positive, in columns (3) and (4), generally the effect of interest in the the cited studies using Tobits. Our result maintains. The standard specification produces statistically significant estimated price elasticities around -1. Our itemizer specification again estimates elasticities close to, and not statistically different from, 0 and significantly less than, in absolute value, -1 from the itemizer model.

Finally we check the robustness of our results to the exclusion of other itemizable expenditures (E). As noted above non-donation E will be correlated with price via itemization status and likely correlated with donations and there fore its omission, as is done throughout the literature, will results in a biased estimator of the price elasticity. Including E, however, might be problematic as donations and non-donation deductible expenditures may be co-determined though this may be mitigated by the fact that more than half of non-donation deductible expenditures are accounted for by mortgage interest payments and real estate taxes (Lowry 2014) which are likely to be pre-determined in most cases. The role of E in estimating the price elasticity of giving has received very little attention in the literature. E is not generally available in survey data and is therefore omitted and the studies using tax-filer data have not addressed this issue to our knowledge.[31] In Table 7 we present results analogous to those presented in Table 3 above, but obtained excluding log E from the model.

Table 7: Robustness checks IV, Excluding other itemizable expenditures (E)

	(1)	(2)	(3)	(4)
	Standard model	IV with $\tau_{it}^s - \tau_{it}^b$	IV with $\Delta\tau_{it}^b$	Itemizer model
$\Delta \log P^b$	-1.358***	-0.307	0.178	0.037
	(0.192)	(2.321)	(0.685)	(0.312)
Δitemizer				0.484***
				(0.094)
Observations	19342	19342	19342	19342
R^2	0.019	0.013	0.010	0.020
H_0 : IV estimator is identified		0.000	0.000	
$H_0 : \beta_{\Delta Logprice} < -1$	0.969	0.765	0.085	0.000

Notes: Results in column (1) are obtained from OLS-FD estimation of equation (3). Results in columns (2) and (3) are from 2SLS-FD estimation of equation (3) using $\tau_{it}^s - \tau_{it}^b$ and $\Delta\tau_{it}^b$ as the instrument, respectively. Results in column (4) are from OLS-FD estimation of equation (7). All standard errors are clustered (at the household level). The penultimate row shows the p-value from the first stage F-test. The tests reported in the last row is the one-sided t-tests of the estimated price elasticities being elastic (≤ -1) against the alternative hypothesis that the donations are price inelastic. Stars indicate statistical significance according to the following schedule: *** 1%, ** 5% and * 10%.

Again, our result maintains as the estimated price elasticities are not sensitive to the exclusion of E. While such robustness checks are not exhaustive, the stability of our result to variation in data transformation, estimation sample, estimator and specification provides further support of our main result.

4.2 Testing for a Non-Linear effect of $\Delta \log (P_{it})$

We next consider the possibility of a non-linear price effect. Note that the large positive estimate of γ of 0.45, see Table 3 suggests (conditional ΔX_{it}) average log donations of start and stop itemizers

[31] Note that a full and formal treatment of the simultaneous nature of the determination of E and D is beyond the scope of the current paper. The fact that our empirical results are not sensitive to the inclusion or exclusion of E suggests that concerns over endogeneity bias arising from the co-determination of E and D or the omission of E may be minor in practice.

relative to non-switchers is $+0.45$ and -0.45, respectively, which corresponds with the intuition in Section 2. At first sight this could be seen as the donors' response to the price change from the change in itemization status, and hence part of the true price effect. However, by the discussion in Section 2 we know that γ must be greater than zero and reflects the response to endogenous price changes of switchers, not purely a true price effect. It may be the case that the price response for switchers differs to non-switchers, in this case γ may indeed pick up some genuine responsiveness of donations to changes in the price, and we may overestimate the bias. Section 4.1 considers this point by considering non-linear generalizations of our model.

While controlling for itemization status allows us to consistently estimate the price elasticity of giving for the average taxpayer as seen above further complications arise if there are other problems with the standard specification of the donations model (equation (3)). Another key restriction of Equation (3) is that the price effect is assumed to be linear in $\Delta\log(P_{it})$ and is the same for switchers and continuous itemizers. However, if the response (*ceteris paribus*) to a, say, 30% price drop is more than 10 times the change from a 3% price drop, then the intercept would shift for switchers even aside from a bias in the standard model. In this case part of γ will explain the endogenous movement in $\Delta\log(P_{it})$ and part will pick up a genuine omitted price response.

There are economic reasons to think the response to a change in P coming from a change in itemization status may differ from the response to a change in P from changes in the marginal tax rate. Such an 'itemization effect' was posited early in the literature (Boskin and Feldstein, 1977). Dye (1978) points out that tax payers are more likely to know their itemization status than their marginal tax rate. The change induced in P by a change in itemization status is large and thus likely to be more salient, whereas changes in the marginal tax rate can be very small. Dye estimates a specification very similar to the itemizer specification we derive. He, like us, finds that the itemization status is a highly significant determinant of giving. However, Dye misinterprets this estimated effect, claiming that the identified price effect in the literature is really an itemization effect and failing to attribute any of the estimated effect to the bias we derive above.[32]

We must therefore be careful how we interpret γ and β in the presence of omitted non-linearities. When we control for changes in itemization status the price response we estimate β is the general price response to changes in the marginal tax rate, which are quite small. If there are strong non-linearities we cannot infer that this estimated elasticity reflects the behaviors to larger changes in price. We consider the possibility of an itemization effect and more general non-linearities in the effect of $\Delta\log(P_{it})$ on $\Delta\log(D_{it})$ in our model and results are presented in Table 8.

[32] Despite featuring in some prominent early publications, the 'itemizer effect' has largely been ignored in the literature since, Brown (1987) being an exception.

Table 8: Non-linear effect of $\Delta\log(P_{it})$

	(1)	(2)	(3)	(4)	(5)
	Switchers	Quadratic	$\|\Delta\log P\|>0.15$	$\|\Delta\log P\|>0.25$	$\|\Delta\log P\|>0.36$
$\Delta\log P$	0.003	-0.049	0.021	-0.058	-0.060
	(0.362)	(0.315)	(0.300)	(0.298)	(0.294)
Δitemizer	0.433***	0.452***	0.461***	0.451***	0.450***
	(0.141)	(0.096)	(0.089)	(0.089)	(0.089)
Switcher$\times\Delta\log P$	-0.128				
	(0.606)				
$\Delta\log P^2$		0.010			
		(0.502)			
$\Delta\log P\times 1(\|\Delta\log P\| > 0.15)$			-0.142		
			(0.123)		
$\Delta\log P\times 1(\|\Delta\log P\| > 0.25)$				-0.038	
				(0.146)	
$\Delta\log P\times 1(\|\Delta\log P\| > 0.36)$					-0.054
					(0.173)
Observations	19342	19342	19342	19342	19342
R^2	0.020	0.020	0.018	0.018	0.018
$H_0 : \beta_{\Delta \text{Log} P} \leq -1$	0.045	0.001	0.003	0.002	0.002

Notes: All standard errors are clustered (at the household level). The tests reported is the one-sided t-tests of the estimated price elasticities being elastic (≤ -1) against the alternative hypothesis that the donations are price inelastic. Stars indicate statistical significance according to the following schedule: *** 1%, ** 5% and * 10%.

In column (1) we re-estimate the itemizer model but allow the price elasticity to differ for those who start or stop itemizing ('switchers'). The estimated price elasticity for this sub-sample ($\hat{\beta} = -0.225$, 95 percent confidence interval: -1.258 to 0.808) does not significantly differ from that of non-switchers or from 0. However, we cannot reject the null hypothesis that donations are price elastic for switchers either due to the larger standard error. As such it might be that those in the general population respond strongly to changes in itemization status (which are the largest changes in price) and less so to a change in price from a change in tax rates which are smaller and less salient. Given the higher imprecision of the estimator, due to the high correlation (multicollinearity) between ΔI and $Switcher \times \Delta\text{log}P$ ($\hat{\rho} = -0.936$), it is difficult to identify the price elasticity for switchers.

In column (2) we include the square of $\Delta\log(P_{it})$ as an additional regressor but find no evidence of a quadratic relationship. We then interact $\Delta\log(P_{it})$ with dummies taking a value of 1 if $\Delta\log(P_{it})$ is in the top quartile of the $\Delta\log(P_{it})$ distribution (column (3)), in the top decile (column (4)) or in the top percentile (column (5)). In each case the coefficient on the interaction terms is close to 0 and statistically insignificant at conventional levels.

If there were a strong itemization or non-linear price effect we would expect the estimate of γ to reduce quite sharply. However, we find estimates of γ are very stable around 0.45 even when allowing for different possible non-linearities in $\Delta\log(P_{it})$. As such we conclude that we have not likely overstated the bias found in Table 3 by ommiting potential non-linear price effects.

4.3 Price effects by income class

Studies using tax-filer data do not suffer from the bias derived in Theorem 1. An example of this kind of study is Bakija and Heim (2011) who find evidence of a price elasticity in around -1. Itemizers are, on average, higher income earner than non-itemizers. For example, the sample of itemizers in Bakija and Heim has a mean income of about $1 million. As such, it is not clear the degree to which the price effect found in Bakija and Heim, and elsewhere (e.g. Randolph (1995), Auten et al. (2002) is due to those people being itemizers or higher income earners.

Some researchers (Feldstein and Taylor, 1976; Reece and Zieshang, 1985) have found the economically counter-intuitive result that the price elasticity is largest for those with lowest incomes. Peloza and Steel (2005) find that the price elasticities for higher income donors seem to be slightly greater than, though not significantly different from, those for lower income donors. Bakija and Heim (2011) find little evidence the the magnitude of the price effect varies with income, though their sample is disproportionately wealthy even for tax-filer data.

In Table 9 we present some descriptive statistics for taxable income decile groups.[33] Note that while the probability of being a continuing itemizer increases monotonically with income, the probability of switching itemization status rises with income and then falls. We return to this feature below. In column (6) we show the results of the test of the restriction outlined in Theorem 2. The restriction holds for every decile group. In the analysis that follows we combine the bottom two decile groups due to the lack of price variation among the lowest income earners. As can be seen in Table 9, the variance of $\Delta\log(P_{it})$ at the bottom of the income distribution is about one-sixth that at the top making identification of the price effect difficult for these relatively poorer households.[34]

Table 9: Descriptive statistics by income

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Mean income ($'000)		P[Switcher]	P[Cont. itemizer]	Var[$\Delta\log P$]	$H_0 : \bar{\tau}_1 = \bar{\tau}_{-1}$
	Non-Itemizers	Itemizers				
1	23.885	25.533	0.106	.0383076	0.006	0.200
2	34.663	35.878	0.159	.0938511	0.012	0.337
3	43.261	45.986	0.200	.1494014	0.014	0.555
4	52.640	54.973	0.243	.187722	0.015	0.757
5	61.003	63.172	0.261	.2787457	0.019	0.415
6	70.422	75.351	0.257	.3457213	0.021	0.838
7	82.666	86.848	0.263	.4483441	0.026	0.153
8	93.988	101.440	0.219	.5449605	0.028	0.281
9	119.766	123.442	0.195	.6335157	0.030	0.444
10	198.881	216.647	0.168	.7482555	0.035	0.921

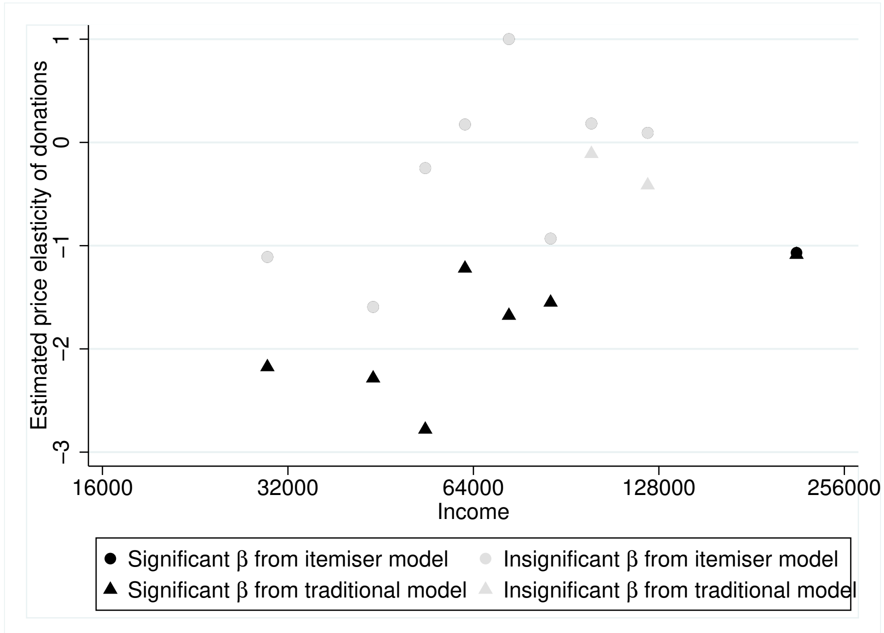
Notes: This table presents some relevant descriptive statistics by income decile group. These income groups, but combining the bottom two decile groups form the basis of Figures 2, 3 and 4.

In Figure 2 we plot the estimated price elasticities from both the standard model and the itemizer model across these income groups.

[33] To avoid losing observations that become singletons when the sub-samples are defined, we calculate the mean net household income over the observed period and then estimate the model for different levels of mean household income ($\bar{y_i}$) rather than annual income (y_{it}).

[34] Our results are very similar if we keep the bottom two decile groups but we get very large standard errors for the bottom decile group which wash out some of the features we are interested in showing in Figure 4 below.

Figure 2: Variation in estimated price elasticities over income



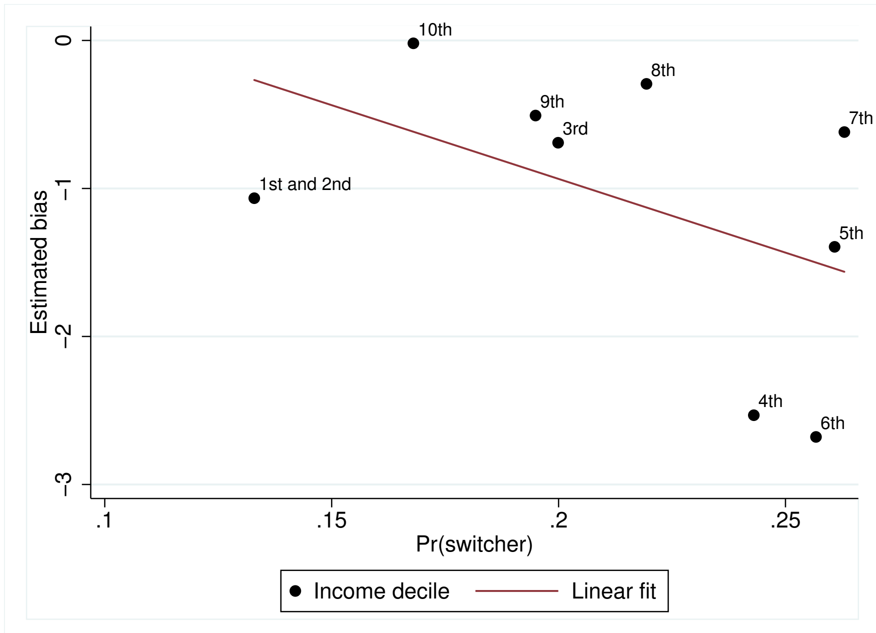
Notes: The markers plot $\hat{\beta}_{FD}$ (triangles) and $\hat{\beta}^{I}_{FD}$ (circles) for each income group (bottom quintile, upper eight deciles). Grey markers are statistically insignificant at the 10 percent level and black markers are significant at the 10 percent level.

Black and grey markers indicate that we reject and accept the null hypothesis that $\beta = 0$ respectively (at the 10 percent) against the alternative that $\beta < 0$ within the various income deciles. Estimates from the standard model are triangles and the circles are estimates from the itemizer model. With the standard model, we find large and significant price elasticities for the bottom quintile and the next five decile groups as well as for the top decile group. The estimated price elasticities for the eighth and ninth decile groups are close to, and not statistically different from, 0. These results suggest a non-linear relationship between the price responsiveness of taxpayers and their income with lower/middle income taxpayers as well as the wealthiest taxpayers being sensitive to changes in the price of giving. In contrast, the results from the itemizer specification suggest that the bottom 90 percent of the income distribution is not sensitive to changes in the price of giving. We do find some evidence that the highest income earners are sensitive as the estimated elasticities for the top decile (p-value=0.088) group is significant. Note that the estimate from the itemizer model lies below that of the the standard model save for the top decile group where the estimates are virtually equivalent.

We fail to reject the required restriction for the consistency of the itemizer model i.e. $\bar{\tau}_1 = \bar{\tau}_{-1}$ for every decile group (see the last column of Table 9, discussed below). As such, by Theorem 1 and 2 (now across each decile) the difference between the estimated income elasticities in each model is a consistent estimator of the bias in the price elasticity within each income decile from the standard model. The mean of the estimated biases over the decile groups is -1.06 and is largest (in absolute value) for the middle deciles, where the probability of switching status is highest.

Below we plot the size of the estimated bias ($\hat{\beta}_{FD} - \hat{\beta}^{I}_{FD}$) against the probability of switching within each income decile group.

Figure 3: Estimated bias plotted against probability of switching itemization status across income decile groups



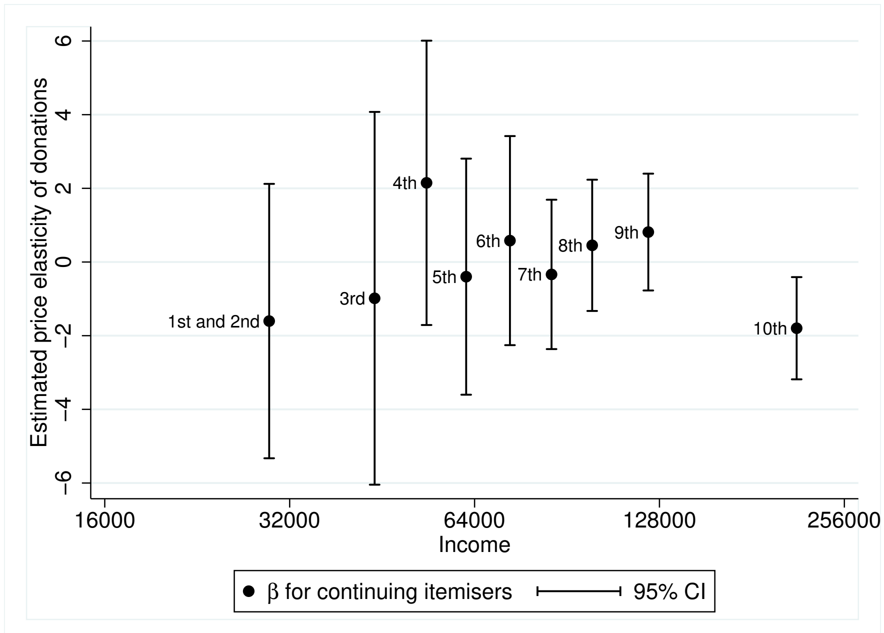
Notes: The markers plot $\hat{\beta}_{FD} - \hat{\beta}^{I}_{FD}$ by the probability of switching itemization status in each income group (bottom quintile, upper eight deciles). The line is the linear fit to these points.

By Theorem 1 the size of the bias increases in p_1, p_{-1} and decreases in Var(Δlog$P$) for a given ξ_1, ξ_{-1} which are unobservable (though we know are both negative by Theorem 1). If ξ_1, ξ_{-1} were roughly equal across income deciles, or did not move in any systematic way, we should expect to see some negative (though not necessarily linear) relationship between the bias in the OLS estimator in the standard model and the probability of switching across income deciles. We see some support for this in Figure 3 which shows the magnitude of the estimated bias by the probability of switching. The correlation between the probability of switching status and the size of the bias is -0.477.

It is difficult to conceive of an economic rational for the finding in the standard model of why lower income households would be more responsive to tax incentives than richer households. The results and discussion in this section utilizing Theorems 1 and 2 provide some evidence that this finding is at least in part due to a bias for utilizing endogenous price variation from switching itemization status.

While we find evidence that the average taxpayer is not sensitive to changes in the price of giving, it remains the case that previous studies using tax-filer data have regularly found price elasticities close to -1. We find evidence that the average higher income earner, whether itemizer or not, also exhibits sensitivity to changes in the price of giving with price elasticities of around -1 for the top decile group. It is clear, however, that higher income people are also more likely to itemize, as can be seen in Table 9. An obvious question is then whether the significant effects found here for the average high earner and the significant effects found in, for example, Bakija and Heim (2011) are driven by the fact that people are itemizers or higher income earners. As noted above, estimates obtained from tax-filer data are consistent and do not suffer from the bias derived in Theorem 1. To test this we estimate our model for continuing itemizers (equivalent to using tax filer data) over different income decile groups and present results in Figure 4.

Figure 4: Price elasticity by income group for continuing itemizers



Notes: Each marker is the estimated price elasticity of giving for the group (bottom quintile, upper eight deciles). The whiskers show the 95 percent confidence interval around each estimate.

Note from Table 9 that non-itemizers have lower average within decile group income than itemizers (columns 1 and 2).

We find evidence that the highest earning continuing itemizers, those in the top decile group, do exhibit a rather substantial sensitivity to changes in the price of giving with elasticities around -2. Continuing itemizers at lower levels of income do not seem to be sensitive to changes in the price of giving. We estimate the model for all continuing itemizers below the top income decile together and obtain an estimated price elasticity of 0.281 (95 percent confidence interval: -.459 to 1.020) which we find to be statistically different from the estimated price elasticity for continuing itemizers in the top decile of income (p-value=0.008). These results, taken together with those in Figure 2, suggest that it is the fact that one is a higher earner that corresponds to being more sensitive to changes in the price, not simply the fact that a person is an itemizer as we show that the average person (not the average itemizer) in the top income decile is sensitive to price changes but we do not find evidence that lower income itemizers are sensitive to price changes.

5 Conclusions

There is a large literature seeking to estimate the responsiveness of tax payers to changes in the price of giving. Many of those studies use survey data as it includes data on donation behaviors of those in the general population including price variation from changes in itemization status not often seen in tax filer data, which also disproportionately oversample the wealthy. In this paper we show that estimates of the price elasticity utilizing variation in price from changes in itemization status (largely in survey data) produce severely biased estimates, even omitting endogenous itemizers as is done in the literature.

We derive the form of bias of the OLS-FD estimator in the standard model and show a downward bias when agents switch itemization status. It is shown that the approach of instrumenting the change in price with exogenous changes in the marginal tax rate, though identified, produces too standard errors so large as to make economically meaningful inference impossible. To obtain more efficient inference we derive the bias of the OLS estimator of the price elasticity in a model which controls for the change in itemization status, which is a measurable source of endogeneity in the price. We derive and discuss the form of this bias and find empirically with probability close to 1 that this bias is zero. The standard errors of the price elasticity in this estimator are also much smaller than those from 2SLS allowing us to make inference on whether the donations are price elastic.

Empirically we find that the consistent estimates of the price elasticity for the average taxpayer obtained using the itemizer model are not price elastic. However, even in the consistent and efficient OLS estimator the standard errors are fairly large such that the question of whether the price elasticity is closer to 0 or -1 remains open though the lower bound of the 95 percent confidence interval we estimate is -0.75. The bias in the estimator obtained from the standard model in the literature is large, approximately of the order -1. This finding is robust to non-linear generalizations, across difference income deciles, in non-linear Tobit models and more general OLS-WG estimators. Our results suggest that Clotfelter may be right in suggesting that the average tax payer is unlikely to be responsive to the price of giving.

Estimates of the price elasticity in the standard model across different income levels show the size of price elasticity is decreasing (in absolute value) in income. We provide evidence that this perhaps surprising result is at least in part explained by the bias in the estimator of the price elasticity in the standard literature model. Correcting for this bias with the itemizer model we no longer find evidence that lower income households respond most to tax incentives with estimates of the price elasticities in each income decile being closer to, and not significantly different from, 0. We do find evidence that higher income households are indeed responsive. This result differs from the findings in the literature using tax-filer data as our result is for the average taxpayer or average higher income taxpayer where as results from tax-filer data are for the average itemizer. We find that it is the higher income people, who are also more likely to be itemizers, that are sensitive to changes in the price of giving. Itemizers with incomes in the bottom 90 percent of the income distribution do not appear to respond to changes in the price of giving. This suggests it is the fact that people are higher income that corresponds to them being sensitive to changes in the price, not the fact that they itemize.

Considering these results together with the existing work using tax-filer data suggests that a re-thinking of the tax deductibility of donations may be called for. It is well established in the literature that itemizing households are sensitive to changes in the price of giving (e.g. Bakija and Heim, 2011). Evidence from studies using survey data using the standard model find that the average taxpayer is even more responsive to changes in the price than the higher earning itemizers and our comparable results show the same. In fact, using the standard model we find that it is relatively poorer households who are the most sensitive to the price of giving. However, using the itemizer model that we propose we find that the price response is inelastic for the average taxpayer and only find evidence of any response for the average wealthier person (those in the top decile). Lowry (2014) shows that taxpayers claimed $134.5 billion of charitable deductions in 2010, 53 percent of which is from taxpayers with income below $250,000 roughly the same income as the top decile in our data. Our results suggest the cost of tens of billions of dollars in lost tax revenue is not resulting in the benefit found in the literature in the form of increased charitable donations for the average taxpayer and in fact the bottom 90 percent of the income distribution. As such, and given the evidence presented here, the government may consider amending the charitable deduction for those households below the top marginal tax bracket or revising the subsidy in line with Saez (2004).

Appendix A

To simplify the proofs of Theorems 1 and 2 we make the assumption that τ_{it} is independent of u_{it}, which is slightly stronger than the assumption that τ_{it} is strictly exogenous. The results do not hinge on this slight strengthening of the exogeneity assumption, but simplify the proof and exposition.

Proof of Theorem 1

Define $p_1 = \mathcal{P}\{\Delta I_{it} = 1\}$, $p_{-1} = \mathcal{P}\{\Delta I_{it} = -1\}$, $p_0 = \mathcal{P}\{\Delta I_{it} = 0\}$, $\xi_1 = E[u_{it}\Delta \log(P_{it})|\Delta I_{it} = 1]$, $\xi_{-1} = E[u_{it}\Delta \log(P_{it})|\Delta I_{it} = -1]$. Under the i.i.d assumption then by the Khinchine Weak Law of Large Numbers (KWLLN)

$$\hat{\beta}_{FD} \xrightarrow{p} \beta + \frac{E[u_{it}\Delta \log(P_{it})]}{E[\Delta \log(P_{it})^2]} \tag{1}$$

where we now show that

$$E[u_{it}\Delta \log(P_{it})] = p_1\xi_1 + p_{-1}\xi_{-1} \tag{2}$$

where both $\xi_1, \xi_{-1} < 0$ which establishes the result.

We use the Law of Iterated Expectations (LIE) to re-write $E[u_{it}\Delta \log(P_{it})]$ as a weighted sum of the conditional expectations $u_{it}\Delta \log(P_{it})$ for I1-I4 itemizers defined in Section 2.

Firstly note that when $\Delta I_{it} = 0$ and $I_{it} = I_{i,t-1} = 0$ (I4) then $\Delta \log(P_{it}) = 0$ and for $I_{i,t} = I_{i,t-1} = 1$, $\Delta \log(P_{it}) = \Delta \log(1 - \tau_{it})$ so

$$E[u_{it}\Delta \log(P_{it})|\Delta I_{it} = 0] = E[u_{it}|I_{it} = I_{i,t-1} = 1]E[\Delta \log(1 - \tau_{it})|I_{it} = I_{i,t-1} = 1]p_{0,1} \tag{3}$$

as u_{it} is assumed independent of $\Delta \log(1 - \tau_{it})$ where $p_{0,1} = \mathcal{P}\{I_{it} = I_{i,t-1} = 1\}$ and

$$E[u_{it}|I_{it} = I_{i,t-1} = 1] = E[u_{it}|E_{it} > S_{it}, E_{i,t-1} > S_{i,t-1}] = E[u_{it}] = 0 \tag{4}$$

since $\omega = 0$. More generally when $\omega \neq 0$ then the same result follows assuming $E[u_{it}|E_{it}] = E[u_{it}]$ which could be achieved by controlling for (polynomials of) E_{it}.

By the LIE utilizing $E[u_{it}\Delta \log(P_{it})|\Delta I_{it} = 0] = 0$ we can re-express

$$\begin{aligned} E[u_{it}\Delta \log(P_{it})] &= E[\log(1 - \tau_{it})u_{it}|\Delta I_{it} = 1]p_1 - E[\log(1 - \tau_{i,t-1})u_{it}|\Delta I_{it} = -1]p_{-1} && (5) \\ &= \xi_1 p_1 + \xi_{-1} p_1. && (6) \end{aligned}$$

noting $\Delta \log(P_{it}) = \log(1 - \tau_{it})$ for $\Delta I_{it} = 1$ and $\Delta \log(P_{it}) = -\log(1 - \tau_{i,t-1})$

The event $\Delta I_{it} = 1$ (I2) is equivalent to $E_{it} \geq S^*_{it}$ (itemizer at time t) and $D_{i,t-1} \leq S_{i,t-1} - E_{i,t-1}$ (non-itemizer time t-1) so that

$$\Delta \log D_{it} \geq \log(D_{it}) - \log(S_{i,t-1} - E_{i,t-1}) \tag{7}$$

where $\Delta \log D_{it} = \beta \log(1-\tau_{it}) + u_{it}$ (as $\Delta \log(P_{it}) = \log(1-\tau_{it})$) so that

$$\begin{aligned} u_{it} &\geq \log(D_{it}) - \log(S_{i,t-1} - E_{i,t-1}) - \beta \log(1-\tau_{it}) & (8) \\ &\geq -\log(S_{i,t-1} - E_{i,t-1}) - \beta \log(1-\tau_{it}) & (9) \end{aligned}$$

where (8) follows as $\log(D_{it}) \geq 0$ as $D_{it} = D_{it}^* + 1$ where $D_{it}^* \geq 0$. Define $h_{it} := -\log(S_{i,t-1} - E_{i,t-1}) - \beta \log(1-\tau_{it})]$ then

$$\begin{aligned} E[u_{it}|\Delta I_{it} = 1] &= E[u_{it}|u_{it} \geq h_{it}, E_{it} \geq S_{it}] & (10) \\ &\geq E[u_{it}|u_{it} \geq h_{it}] & (11) \\ &> 0 & (12) \end{aligned}$$

where (11) follows by (9) and noting E_{it} is mean independent of u_{it}. The final inequality follows as $E[u_{it}] = 0$, where defining $p_{11} = \mathcal{P}\{u_{it} \geq h_{it}\}$

$$0 = E[u_{it}] = E[u_{it}|u_{it} \geq h_{it}]p_{11} + E[u_{it}|u_{it} \leq h_{it}](1-p_{11}) \quad (13)$$

where $E[u_{it}|u_{it} \leq h_{it}] < 0$ as $h_{it} \leq 0$ (as $\beta \leq 0$ and $E_{i,t-1} - S_{i,t-1} \leq 1$ as $I_{i,t-1} = 0$) and‘ since $E[u_{it}|u_{it} \leq h_{it}] = E[u_{it}|u_{it} \leq h_{it}, h_{it} = 0] \Pr\{h_{it} = 0\} + E[u_{it}|u_{it} \leq h_{it}, h_{it} < 0] \Pr\{h_{it} < 0\}$ since $\Pr\{h_{it} < 0\} > 0$ and

$$E\left[u_{it}|u_{it} \geq h_{it}\right] > 0 \quad (14)$$

follows from (13) noting that $0 < p_{11} < 1$. Finally since $\log(1-\tau_{it}) < 0$. for all i,t and is strictly less than zero for some i,t then

$$E[\log(1-\tau_{it})|\Delta I_{it} = 1] < 0. \quad (15)$$

By independence of τ_{is} and u_{it}

$$E[\log(1-\tau_{it})u_{it}|\Delta I_{it} = 1] = E[\log(1-\tau_{it})|\Delta I_{it} = 1]E[u_{it}|\Delta I_{it} = 1] \quad (16)$$

where (14) and (16) imply

$$E[\log(1-\tau_{it})u_{it}|\Delta I_{it} = 1] \leq E[\log(1-\tau_{it})|\Delta I_{it} = 1]E[u_{it}|u_{it} \geq h_{it}] \quad (17)$$

where together with the inequality in (15) implies

$$\xi_1 := E[\log(1-\tau_{it})u_{it}|\Delta I_{it} = 1] < 0. \quad (18)$$

A similar argument holds in reverse for second term in the RHS of (6) for $\Delta I_{it} = -1$ where

$$\xi_{-1} := -E[\log(1-\tau_{i,t-1})u_{it}|\Delta I_{it} = -1] < 0. \quad (19)$$

establishing the result.

Proof of Theorem 2

We specify our itemizer specification (equation (3) in the Section 2)

$$\Delta \log(D_{it}) = \gamma \Delta I_{it} + \beta \Delta \log(P_{it}) + \omega' \Delta X_{it} + e_{it} \tag{20}$$

where X_{it} is a $k \times 1$ vector of controls and $u_{it} = e_{it} + \gamma \Delta I_{it}$. To show the result decompose ΔX_{it}

$$\Delta X_{it} = \Xi z_{it} + v_{it}^{\Delta X} \tag{21}$$

where Ξ is a $k \times 2$ matrix of OLS coefficients where by definition $E[z_{it} v_{it}^{\Delta X'}] = 0$. Plugging (21) in to (20)

$$\Delta \log(D_{it}) = \gamma^* \Delta I_{it} + \beta^* \Delta \log(P_{it}) + \omega' v_{it}^{\Delta X} + e_{it} \tag{22}$$

where $\gamma^* = \gamma + \omega' \Xi_1$, $\beta^* = \beta + \omega' \Xi_2$ where Ξ_j is the j^{th} column of Ξ for $j = \{1, 2\}$. We see in the population regressions in (20) and (22) that

$$\beta = \beta^* - \omega' \Xi_2 \tag{23}$$

likewise it is straightforward to show that the sample estimator satisfies

$$\hat{\beta}_{FD}^{I} = \hat{\beta}_{FD}^{I,*} - \hat{\omega}_{FD}^{I,*'} \hat{\Xi}_2 \tag{24}$$

where $\hat{\beta}_{FD}^{I,*}$, $\hat{\omega}_{FD}^{I,*}$ are the OLS estimators in (22) and $\hat{\Xi}_2$ is the estimator of Ξ_2 from OLS regression in (21). Namely we have 'partialled out' ΔX_{it}. Below we show the following two results

$$\hat{\beta}_{FD}^{I,*} \to \beta^* + \frac{p_1 p_{-1}}{C} (\bar{\tau}_1 - \bar{\tau}_{-1})(E[e_{it} | \Delta I_{it} = -1] + E[e_{it} | \Delta I_{it} = 1]) \tag{25}$$

$$\hat{\omega}_{FD}^{I,*} \to \omega \tag{26}$$

where $\hat{\Xi}_2 \xrightarrow{p} \Xi_2$ by KWLLN together this result along with the fact that $\beta = \beta^* - \omega' \Xi_2$ and the results in (29), (25) and (26) imply

$$\hat{\beta}_{FD}^{I} \xrightarrow{p} \beta + \frac{p_1 p_{-1}}{C} (\bar{\tau}_1 - \bar{\tau}_{-1})(E[e_{it} | \Delta I_{it} = -1] + E[e_{it} | \Delta I_{it} = 1]). \tag{27}$$

To show (25) and (26) define $w_{it}^* = (z_{it}', v_{it}^{\Delta X'})'$ and the OLS estimator in (22)

$$\hat{\theta}_{FD}^{I,*} := \left(\sum_{i=1}^{N} \sum_{t=2}^{T} w_{it}^* w_{it}^{*'} \right)^{-1} \sum_{i=1}^{N} \sum_{t=2}^{T} w_{it}^* \Delta \log(D_{it}) \tag{28}$$

where $\hat{\theta}^{I,*}_{FD} := (\hat{\gamma}^{I,*}_{FD}, \hat{\beta}^{I,*}_{FD}, \hat{\omega}^{I,*'}_{FD})'$. Under the i.i.d assumption by an application of KWLLN

$$\begin{aligned}
\hat{\theta}^{I,*}_{FD} &\xrightarrow{p} E[w^*_{it} w^{*'}_{it}]^{-1} E[w^*_{it} \Delta \log(D_{it})] && (29)\\
&= \begin{pmatrix} \gamma^* \\ \beta^* \\ \omega \end{pmatrix} + \begin{pmatrix} E[z_{it} z'_{it}] & E[z_{it} v^{\Delta X'}_{it}] \\ E[v^{\Delta X}_{it} z'_{it}] & E[v^{\Delta X}_{it} v^{\Delta X'}_{it}] \end{pmatrix}^{-1} \begin{pmatrix} E[e_{it} z_{it}] \\ E[e_{it} v^{\Delta X}_{it}] \end{pmatrix} && (30)\\
&= \begin{pmatrix} \gamma^* \\ \beta^* \\ \omega \end{pmatrix} + \begin{pmatrix} E[z_{it} z'_{it}]^{-1} & 0 \\ 0 & E[v^{\Delta X}_{it} v^{\Delta X'}_{it}]^{-1} \end{pmatrix} \begin{pmatrix} E[e_{it} z_{it}] \\ 0 \end{pmatrix} && (31)
\end{aligned}$$

where (30) follows plugging in $\Delta \log(D_{it}) = \gamma^* \Delta I_{it} + \beta^* \Delta \log(P_{it}) + \omega' v^{\Delta X}_{it} + e_{it}$ and (31) follows as $E[e_{it} v^{\Delta X}_{it}] = 0$ and $E[z_{it} v^{\Delta X'}_{it}] = 0$. Hence we establish (26). It follows by (30) (noting $z_{it} = (\Delta I_{it}, \Delta \log(P_{it}))$' that

$$\begin{aligned}
\begin{pmatrix} \hat{\gamma}^{I,*}_{FD} \\ \hat{\beta}^{I,*}_{FD} \end{pmatrix} &\xrightarrow{p} \begin{pmatrix} \gamma^* \\ \beta^* \end{pmatrix} + E[z_{it} z'_{it}]^{-1} E[e_{it} z_{it}] \\
&= \begin{pmatrix} \gamma^* \\ \beta^* \end{pmatrix} + \begin{pmatrix} E[(\Delta I_{it})^2] & E[\Delta I_{it} \Delta \log(P_{it})] \\ E[\Delta I_{it} \Delta \log(P_{it})] & E[(\Delta \log(P_{it}))^2] \end{pmatrix}^{-1} \begin{pmatrix} E[e_{it} \Delta I_{it}] \\ E[e_{it} \Delta \log(P_{it})] \end{pmatrix} \\
&= \begin{pmatrix} \gamma^* \\ \beta^* \end{pmatrix} + \frac{1}{\det(E[z_{it} z'_{it}])} \begin{pmatrix} E[(\Delta \log(P_{it}))^2] & -E[\Delta I_{it} \Delta \log(P_{it})] \\ -E[\Delta I_{it} \Delta \log(P_{it})] & E[(\Delta I_{it})^2] \end{pmatrix} \begin{pmatrix} E[e_{it} \Delta I_{it}] \\ E[e_{it} \Delta \log(P_{it})] \end{pmatrix}.
\end{aligned}$$

Expanding out the second element in the limit and defining $C = \det(E[z_{it} z'_{it}])$ which is greater than zero by assumption (no multi-collinear instruments)

$$\begin{aligned}
\hat{\beta}^{I,*}_{FD} - \beta^* &\xrightarrow{p} \frac{1}{C} \left(E[e_{it} \Delta \log(P_{it})] E[(\Delta I_{it})^2] - E[\Delta I_{it} \Delta \log(P_{it})] \right) E[e_{it} \Delta I_{it}] && (32)\\
&= \frac{1}{C} ((p_1 + p_{-1}) E[e_{it} \Delta \log(P_{it})]) - (\bar{\tau}_1 p_1 + \bar{\tau}_{-1} p_{-1}) E[e_{it} \Delta I_{it}]) && (33)\\
&= \frac{1}{C} \left((E[e_{it} \Delta \log(P_{it})] - \bar{\tau}_1 E[e_{it} \Delta I_{it}]) \, p_1 + (E[e_{it} \Delta \log(P_{it})] - \bar{\tau}_{-1} E[e_{it} \Delta I_{it}]) \, p_{-1} \right) && (34)\\
&= \frac{1}{C} p_1 p_{-1} (\bar{\tau}_1 - \bar{\tau}_{-1})(E[e_{it} | \Delta I_{it} = -1] + E[e_{it} | \Delta I_{it} = 1]) && (35)
\end{aligned}$$

where $\bar{\tau}_1 = E[\log(1 - \tau_{it}) | \Delta I_{it} = 1]$, $\bar{\tau}_{-1} = E[\log(1 - \tau_{i,t-1}) | \Delta I_{it} = -1]$ and the second equality follows as

$$\begin{aligned}
E[(\Delta I_{it})^2] &= E[(\Delta I_{it})^2 | \left[\Delta I_{it} = 1 \right] p_1 + E[(\Delta I_{it})^2] \,| \Delta I_{it} = -1] p_{-1} \\
&= p_1 + p_{-1}
\end{aligned}$$

$$\begin{aligned}
E[\Delta I_{it} \Delta \log(P_{it})] &= E[\Delta \log(P_{it}) | \Delta I_{it} = 1] p_1 - E[\Delta \log(P_{it}) | \Delta I_{it} = -1] p_{-1} && (36)\\
&= E[\Delta \log(1 - \tau_{it}) | \Delta I_{it} = 1] p_1 + E[\Delta \log(1 - \tau_{i,t-1}) | \Delta I_{it} = -1] p_{-1} && (37)\\
&= \bar{\tau}_1 p_1 + \bar{\tau}_{-1} p_{-1} && (38)
\end{aligned}$$

and the final equality (35) uses the LIE and strict exogeneity of τ_{it} so that

$$E[e_{it}\Delta\log(P_{it})] = E[e_{it}|\Delta I_{it}=1]\bar{\tau}_1 p_1 - E[e_{it}|\Delta I_{it}=-1]\bar{\tau}_{-1}p_{-1} \quad (39)$$

$$E[e_{it}\Delta I_{it}] = E[e_{it}|\Delta I_{it}=1]p_1 - E[e_{it}|\Delta I_{it}=-1]p_{-1} \quad (40)$$

and

$$E[e_{it}\Delta\log(P_{it})] - \bar{\tau}_1 E[e_{it}\Delta I_{it}] = (\bar{\tau}_1 - \bar{\tau}_{-1})E[e_{it}|\Delta I_{it}=-1]p_{-1} \quad (41)$$

where by a similar argument we can show

$$E[e_{it}\Delta\log(P_{it})] - \bar{\tau}_{-1} E[e_{it}\Delta I_{it}] = (\bar{\tau}_1 - \bar{\tau}_{-1})E[e_{it}|\Delta I_{it}=1]p_1. \quad (42)$$

Appendix B

Table B.1: Descriptive statistics for all variables by itemizer type

	(1)	(2)	(3)	(4)	(5)	(6)
	Continuing itemizer	Continuing non-itemizer	Start itemizer	Stop itemizer	itemizer	Non-itemizer
Net taxable income	111074.470	52176.771	81762.902	79279.777	104399.776	54665.756
	(120435.596)	(37126.101)	(61758.096)	(62530.907)	(110785.632)	(43740.458)
Total donation	2076.083	573.042	1192.941	1197.728	1945.228	666.582
	(2606.142)	(1451.247)	(2034.548)	(2650.476)	(2658.242)	(1819.262)
$1 - I\tau^a$	0.765	1.000	0.786	1.000	0.768	1.000
	(0.082)	(0.000)	(0.076)	(0.000)	(0.082)	(0.000)
Age (Head)	47.253	40.572	41.046	43.605	45.444	39.449
	(11.269)	(12.618)	(11.838)	(11.738)	(11.823)	(12.714)
Married^d	0.828	0.512	0.714	0.693	0.785	0.515
	(0.378)	(0.500)	(0.452)	(0.461)	(0.411)	(0.500)
No highschool^d	0.054	0.150	0.107	0.115	0.075	0.150
	(0.226)	(0.357)	(0.309)	(0.319)	(0.264)	(0.357)
Some college^d	0.249	0.260	0.246	0.251	0.246	0.258
	(0.433)	(0.439)	(0.431)	(0.434)	(0.431)	(0.438)
College grad^d	0.266	0.147	0.216	0.203	0.251	0.159
	(0.442)	(0.354)	(0.412)	(0.402)	(0.433)	(0.366)
Graduate school^d	0.213	0.078	0.149	0.136	0.201	0.092
	(0.409)	(0.269)	(0.357)	(0.343)	(0.401)	(0.289)
# of dependent children	0.879	0.793	0.889	0.895	0.878	0.792
	(1.088)	(1.117)	(1.123)	(1.106)	(1.097)	(1.105)
Deductible expenses	19347.317	5539.534	13610.544	11407.217	17827.282	6268.581
	(15423.332)	(6624.256)	(12877.873)	(11089.462)	(15095.168)	(8258.843)
Homeowner^d	0.933	0.450	0.804	0.711	0.893	0.462
	(0.251)	(0.497)	(0.397)	(0.454)	(0.309)	(0.499)
Observations	7630	7704	2195	1877	12515	13776

Notes: All monetary figures are in 2014 prices, deflated using the Consumer Price Index. Standard deviations are shown in ( ). Variables with ^{d} are 0/1 dummies.

There is substantial variation over the dynamic itemizer types (columns (1) to (4)). Continuing itemizers (column (1)) are the most likely to have donated and give the largest donations on average; more than five times that of continuing non-itemizers (column (2)) and more than double the mean donations of start and stop itemizers. Continuing itemizers also have the highest mean income and lowest mean price. The donating probability, mean donation and mean income of the start (column (3)) and stop (column (4)) itemizers are quite similar.

References

[1] Aaron, H. (1972). Federal encouragement of private giving. In *Tax Impacts on Philanthropy*, Princeton. Tax Institute of America.

[2] Andreoni, J., E. Brown, and I. Rischall (1999). Charitable giving by married couples: who decides and why does it matter? *McMaster University Working Paper*.

[3] Angrist, J. and J.-S. Pischke (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, New Jersey: Princeton University Press.

[4] Athey, S. and G. Imbens (2015). A measure of robustness to misspecification. *American Economic Review 105*, 476–80.

[5] Auten, G. E., H. Sieg, and C. T. Clotfelter (2002). Charitable giving, income, and taxes: An analysis of panel data. *The American Economic Review 92*(1), 371–382.

[6] Bakija, J. and B. Heim (2011). How does charitable giving respond to incentives and income? new estimates from panel data. *National Tax Journal 64*(2), 615–650.

[7] Batina, R. G. and T. Ihori (2010). *Public Goods: Theories and Evidence*. Springer.

[8] Benzarti, Y. (2015). *How Taxing Is Tax Filing? Leaving Money on the Table Because of Hassle Costs*. Ph. D. thesis, University of California, Berkeley.

[9] Bönke, T., N. Massarrat-Mashhadi, and C. Sielaff (2013). Charitable giving in the german welfare state: fiscal incentives and crowding out. *Public Choice 154*, 39–58.

[10] Boskin, M. J. and M. S. Feldstein (1977). Effects of the charitable deduction on contributions by low income and middle income households: Evidence from the national survey of philanthropy. *The Review of Economics and Statistics 59*(3), 351–54.

[11] Bradley, R., S. Holden, and R. McClelland (2005). A robust estimation of the effects of taxation on charitable contributions. *Contemporary Economic Policy 23*(4), 545–554.

[12] Brown, E. (1987). Tax incentives and charitable giving: Evidence from new survey data. *Public Finance Quarterly 15*(4), 386–396.

[13] Brown, E. and H. Lankford (1992). Gifts of money and gifts of time estimating the effects of tax prices and available time. *Journal of Public Economics 47*(3), 321–341.

[14] Brown, S., W. Greene, M. Harris, and K. Taylor (2015). An inverse hyperbolic sine heteroskedastic latent class panel tobit model: An application to modelling charitable donations. *Economic Modelling 50*, 321–341.

[15] Brown, S., M. Harris, and K. Taylor (2012). Modelling charitable donations to an unexpected natural disaster: Evidence from the u.s. panel study of income dynamics. *Journal of Economic Behavior and Organization 84*, 97–110.

[16] Clotfelter, C. T. (1980). Tax incentives and charitable giving: Evidence from a panel of taxpayers. *Journal of Public Economics 13*(3), 319–340.

[17] Clotfelter, C. T. (1985). *Federal tax policy and charitable giving*. University of Chicago Press.

[18] Clotfelter, C. T. (2002). The Economics of Giving. In J. Barry and B. Manno (Eds.), *Giving Better, Giving Smarter*. Washington, DC: National Commission on Philanthropy and Civic Renewal.

[19] Dye, R. (1978). Personal charitable contributions: tax effects and other motives. In *Proceedings of the Seventieth Annual Conference on Taxation*, Columbus. National Tax Association-Tax Institute of America.

[20] Emmanuel Saez, J. S. and S. H. Giertz (2012). The elasticity of taxable income with respect to marginal tax rates: A critical review. *Journal of Economic Literature 50*(1), 3–50.

[21] Fack, G. and C. Landais (2010). Are Tax Incentives for Charitable Giving Efficient?: Evidence from France. *American Economic Journal: Economic Policy 2*(2), 117–141.

[22] Fack, G. and C. Landais (Eds.) (2016). *Charitable Giving and Tax Policy: A Historical and Comparative Perspective*. Oxford University Press.

[23] Feenberg, D. and E. Coutts (1993). An introduction to the TAXSIM model. *Journal of Policy Analysis and Management 12*(1), 189.

[24] Feldstein, M. and C. Clotfelter (1976). Tax incentives and charitable contributions in the united states: a microeconometric analysis. *Journal of Public Economics 5*(1-2), 1–26.

[25] Feldstein, M. and A. Taylor (1976). The income tax and charitable contributions. *Econometrica 44*(6), 1201–1222.

[26] Feldstein, M. S. (1995). Behavioral responses to tax rates: Evidence form the tax reform act of 1986. *The American Economic Review 85*(2), 170–174.

[27] Gruber, J. (2004). Pay or pray?: The impact of charitable subsidies on religious attendance. *Journal of Public Economics 88*(12), 2635–2655.

[28] Hansen, L., J. Heaton, and A. Yaron (1996). Finite-sample properties of some alternative gmm estimators. *Journal of Business and Economic Statistics 14*(3), 262–280.

[29] Huck, S. and I. Rasul (2008, October). Testing consumer theory in the field: private consumption versus charitable goods.

[30] Hungerman, D. and M. O. Wilhelm (2016). What is the price elasticity of charitable giving? toward a reconciliation of disparate estimates. *Working Paper*.

[31] Lankford, R. H. and J. H. Wyckoff (1991). Modeling charitable giving using a Box-Cox standard tobit model. *The Review of Economics and Statistics 73*(3), 460–470.

[32] Lowry, S. (2014). Itemized tax deductions for individuals: Data analysis. Technical Report 7-5700, Congressional Research Service.

[33] McClelland, R. and M. F. Kokoski (1994). Econometric issues in the analysis of charitable giving. *Public Finance Review 22*(4), 498–517.

[34] Moffit, R. and M. Wilhelm (2000). Taxation and the labor supply decisions of the affluent. In J. Slemrod (Ed.), *Does Atlas Shrug? The Economic Consequences of Taxing the Rich*. Cambridge University Press.

[35] Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica 46*(1), 69–85.

[36] Olson, N. (2012, December). 2012 annual report to congress. Technical report, National Taxpayer Advocate.

[37] Peloza, J. and P. Steel (2005). The price elasticities of charitable contributions: A Meta-Analysis. *Journal of Public Policy and Marketing 24*(2), 260–272.

[38] Randolph, W. (1995). Dynamic income, progressive taxes, and the timing of charitable contributions. *Journal of Political Economy 103*(4), 709–738.

[39] Reece, W. (1979). Charitable contributions: New evidence on household behavior. *The American Economic Review 69*(1), 142–151.

[40] Reece, W. and K. Zieschang (1985). Consistent estimation of the impact of tax deductibility on the level of charitable contributions. *Econometrica 53*(2), 271–293.

[41] Reinstein, D. A. (2011). Does One Contribution Come at the Expense of Another? *The B.E. Journal of Economic Analysis and Policy 11*(1).

[42] Roberts, R. (1984). A positive model of private charity and wealth transfers. *Journal of Political Economy 92*(1), 136–148.

[43] Saez, E. (2004). The optimal treatment of tax expenditures. *Journal of Public Economics 88*, 2657–2684.

[44] Scharf, K. and S. Smith (2010). The price elasticity of charitable giving: Does the form of tax relief matter? *IFS Working Paper W10/07*.

[45] Slemrod, J. (1988). Are estimated tax elasticities really just tax evasion elasticities? the case of charitable contributions. *The Review of Economics and Statistics 71*(3), 517–22.

[46] Staiger, D. and J. H. Stock (1997). Instrumental variables regression with weak instruments. *Econometrica 65*(3), 557–586.

[47] Steinberg, R. (1990). Taxes and giving: New findings. *Voluntas 1*(2), 61–79.

[48] Taussig, M. (1967). Economic aspects of the personal income tax treatment of charitable contributions. *National Tax Journal 20*(1), 1–19.

[49] Wilhelm, M. O. (2006). New data on charitable giving in the PSID. *Economics Letters 92*(1), 26–31.

[50] Wilhelm, M. O. (2007). The quality and comparability of survey data on charitable giving. *Nonprofit and Voluntary Sector Quarterly 36*(1), 65–84.

[51] Yöruk, B. (2010). Charitable giving by married couples revisited. *The Journal of Human Resources 45*(2), 497–516.

[52] Yöruk, B. (2013). The impact of charitable subsidies on religious giving and attendance: Evidence from panel data. *The Review of Economics and Statistics 95*(5), 1708–1721.

[53] Zampelli, E. and S. Yen (2017). The impact of tax price changes on charitable contributions. *Contemporary Economic Policy 35*(1), 113–124.