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Abstract

There is an extensive literature that seeks to estimate the effect of tax incentives for charitable giving in United States. We provide theoretical and empirical evidence of a large downward bias in the estimator of the price (or tax-price) elasticity using survey data when non-itemizers are included in the sample. Such studies account for nearly half of the published work in this area and have generally found price elasticities in excess of -1 and larger (in absolute value) than those found using samples of itemizers from tax-filer data. We provide an intuitive modification to the standard model which we show yields a consistent and efficient estimator of the price elasticity for the average tax payer under a simple testable restriction. We find empirical support for this restriction and estimate a bias in the price elasticity in the standard model of around -1 indicating that the estimates of the price elasticity for the average taxpayer have been systematically over-estimated. Our results suggest an inelastic tax-price elasticity for the average taxpayer where only for those individuals with income in the top decile do we find a statistically significant price elasticity of a magnitude consistent with those estimated on tax-filer data.

Keywords: Charitable giving, tax incentives, bias.

JEL Codes: D64, H21, H24, D12

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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. 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 payments, 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 taxable income. The deductibility of donations has long been recognized as producing 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 sizeable 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 strong 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 efficient estimator of the tax-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. We do find evidence that higher income earners are responsive to changes in the price of giving. 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, is eight times larger than with a price elasticity of -0.5, which we cannot reject.

In general, estimates of the tax 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 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

[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, though some have argued that the threshold ought to be larger (in absolute value) due to concerns about evasion (Slemrod, 1988) while others argued that the deduction might be efficient even at price elasticities smaller than -1 (Roberts, 1984).

[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.

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 surveyed) produce a price elasticity of -1.08 compared to a mean elasticity of -1.29 from studies using survey data, suggesting the average taxpayer is more responsive to changes in the price of giving than the wealthier itemizers.[4] Results in the current paper provide a simple explanation for this unusual finding with evidence that the estimates of the price elasticity obtained from survey data utilizing variation in itemization status suffer from a severe downward bias.

The bias we address in this paper is the inverse of a well-documented problem in the literature. 'Endogenous itemizers' (Clotfelter, 1980) are people that, conditional on other deductible expenditures, are itemizers only because of the level of their donation. A common solution to this issue in the literature has been to omit endogenous itemizers, generally a small share of a sample, leaving only non-itemizers and exogenous itemizers in the estimation sample (e.g. Randolph, 1995; Bakija and Heim, 2011).[5] In studies using tax-filer data this exclusion is sufficient to expunge this endogeneity.

However, this approach is not sufficient to expunge endogeneity when non-itemizers are included in the estimation sample, as is generally the case with survey data. This is because the price of donating for non-itemizers is a function of their donations, just as it is for 'endogenous itemizers'. Non-itemizers face an upper bound on their donations (being less than the standard deduction minus other deductible expenditure) where as exogenous itemizers face no such bound. As such the mean donation for itemizers will be larger than that for non-itemizers by construction. With panel data, the difference in mean donations between itemizers and non-itemizers could be picked up in the fixed effect if people either always itemize or never itemize. In practice, however, there are also people who itemize in some years and not in others and this switching is problematic. For example, if 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. So, for those switching itemization status, 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 were made entirely at random. Below we prove this assertion formally showing that the inclusion of these 'switchers' in the estimation sample introduces a downward bias into the estimator of the price elasticity even when endogenous itemizers are omitted.

A natural solution to address this bias would be to instrument changes in price with the exogenous change in the marginal tax rate (conditional on a given level of income). We pursue this instrumental

[4] In Batina and Toshihiro (2010), another survey of this literature, the mean price elasticity for tax filer studies is -1.25 and is -1.62 in studies using survey data. More recently, Bakija and Heim (2011) find elasticities very close to -1 using a panel of tax filer data and both Yöruk (2010) and Reinstein (2011) find price elasticities in excess 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 they note are "consistent with the body of literature" (p. 11).

[5] Other authors have used predicted itemization status (e.g. Reece, 1979; Reinstein, 2011) to deal with the endogeneity of itemization status. This might expunge some of the bias from 'endogenous itemizers' though will introduce model mispeficiation.

variable (IV) approach and find evidence the instrument is identified, though the IV yields standard errors too large to make any economically meaningful inference. Instead we seek a different approach, noting that in this particular case the source of the endogenous price variation is measurable. We show formally that the Ordinary Least Squares (OLS) estimator of the price elasticity in a model which controls for change in itemization removes this bias when the average change in price for those who stop and start itemizing are of the same magnitude. 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 IV estimator. In fact, we find the standard errors on the estimator of the price elasticity in this model to be one-third of those obtained via Two Stage Least Squares (2SLS).

The paper proceeds as follows. Section 2 provides the formal theoretical results where Section 3 discusses and summarizes the data and Section 4 presents the empirical results. Finally, conclusions are drawn in Section 5. Proofs of the theoretical results along with extra empirical output is provided in appendices.

2 Estimating Price Elasticities of Donation on Survey Data

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

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

$$P_{it} = 1 - I_{it}\tau_{it} \tag{2}$$

$$I_{it} = 1(D_{it} + E_{it} > S_{it}) \tag{3}$$

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 and E_{it} is all other tax deductible expenditure, τ_{it} is the marginal rate, X_{it} is a vector of personal characteristics including income and α_i is all time invariant unobserved heterogeneity.[6] Equation (3) simply states that if the sum of deductible expenditures $(D_{it} + E_{it})$ is larger than the standard deduction (S_{it}) then the person itemizes.[7]

At any time people are either exogenous itemizers ($I_{it} = 1$ where $E_{it} > S^*_{it}$), endogenous itemizers ($I_{it} = 1$ where $D_{it} + E_{it} > S_{it}$ and $E_{it} \leq S^*_{it}$) or non-itemizers ($I_{it} = 0$, i.e $D_{it} + E_{it} \leq S_{it}$). Including

[6] As 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.

[7] 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.

endogenous itemizers in the estimation sample will bias estimates of β. As noted above, a common solution to this issue in the literature has been to omit endogenous itemizers, generally a rather small share of a 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 other side of the endogenous itemizer problem 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 that even when omitting endogenous itemizers a large bias remains as a result of switchers (households itemizing in some years and not in others) and that this bias is not expunged by the inclusion of individual fixed effects when some agents change itemization status.

To show this issue we consider a model where endogenous itemizers are omitted (as is commonly done in the literature) and individual effects (α_i) are removed via first differencing (FD).[8] We omit endogenous itemizers to show the bias remains even when they are excluded.[9] First differencing equation (1) gives

$$\Delta \log(D_{it}) = \beta \Delta \log(P_{it}) + \omega' \Delta X_{it} + u_{it} \tag{4}$$

where $u_{it} = \Delta \epsilon_{it}$.

There are three sources of price variation: 1) changes in taxable income (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 is 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:** $\Delta I_{it} = 0$, $I_{i,t-1} = 0$, $I_{it} = 0$.

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

[8] 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.

[9] A similar result could be found including all types of itemizers but is omitted to show that endogenous price variation remains by including non-itemizers, which has not been.

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 $\Delta I_{it} = 1$ (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,

$$\begin{aligned} \Delta I_{it} = 1 \;\Rightarrow\; \Delta\log(D_{it}) &\geq \log(D_{it}) - \log(S_{i,t-1} - E_{i,t-1}) && (5)\\ &\geq -\log(S_{i,t-1} - E_{i,t-1}) && (6) \end{aligned}$$

where (6) 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 $\Delta\log(D_{it})$ by construction, irrespective of the true price responsiveness of the donor. This negative correlation would emerge even if donations and income (and thus τ_{it}) were randomly assigned.

Following the argument above, Theorem 1, derived formally in Appendix A, shows the OLS-FD estimator of β in (4) is downward biased in the presence of switchers. For ease of exposition we assume $\omega = 0$.[11] Equation (4) then collapses to

$$\Delta\log(D_{it}) = \beta\Delta\log(P_{it}) + u_{it} \tag{7}$$

and the OLS-FD estimator of β in (7) 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 $(D_{it}, \tau_{it}, u_{it})$ are i.i.d.[13] We also assume that τ_{it} is strictly exogenous. However, 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 the change in price and u_{it}, violating the exogeneity condition. We check the robustness

[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 $D_{it} = D^*_{it} + 1$.

[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 (7) 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.

of our results to non-linear specification 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 $\hat{\beta}_{FD} \xrightarrow{p} \beta + \frac{p_1\xi_1 + p_{-1}\xi_{-1}}{E[(\Delta\log(P_{it}))^2]}$ 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 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 relied upon to estimate price elasticities of giving in the past (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. However, though we show this instrument is identified, the correlation between $\Delta\tau$ and $\Delta\log(P_{it})$ is small and the inefficient IV estimator 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 isn't 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 as much of the exogenous price variation as possible with which to consistently estimate β with more precision than the 2SLS-FD estimator.[17]

[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.

[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.

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 (4) which controls for ΔI_{it}, as

$$\Delta \log(D_{it}) = \gamma \Delta I_{it} + \beta \Delta \log(P_{it}) + \omega' \Delta X_{it} + e_{it}. \tag{8}$$

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'

$$\hat{\theta}^{I}_{FD} = \left(\sum_{i=1}^{N} \sum_{t=2}^{T} w_{it} w_{it}' \right)^{-1} \sum_{i=1}^{N} \sum_{t=2}^{T} w_{it} \Delta \log(D_{it}) \tag{9}$$

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

Intuitively the coefficient γ allows the mean change in donations for start and stop itemizers (conditional 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 (4).

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', 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. In which case γ would partly pick up this price effect, and we may overstate the bias. This issue is discussed more in Section 4.1.[18]

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

$$\hat{\beta}^{I}_{FD} \xrightarrow{p} \beta + \frac{p_1 p_{-1}}{C} (\bar{\tau}_1 - \bar{\tau}_{-1})(E[e_{it}|\Delta I_{it} = -1] + E[e_{it}|\Delta I_{it} = 1]). \tag{10}$$

By Theorem 2 (formally proven in Appendix A) there is no bias when either p_1 or p_{-1} are zero, which 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

[18] 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.

($\bar{\tau}_1 = \bar{\tau}_{-1}$) 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

We use data from the Panel Study of Income Dynamics (PSID), a bi-annual survey of American households. The PSID contains information on socio-economic household characteristics, with substantial detail on 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.[19]

We use seven waves of the PSID covering 2000-2012 (biannually) yielding a raw sample with 58,993 observations.[20] 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 for an average of 5.4 years). The unit of analysis is the household. All monetary figures are in 2014 prices.[21]

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).[22] 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.[23]

To help clarify the intuition of the bias in the standard model 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.

[19] Wilhelm (2006, 2007) contend 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.

[20] 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.

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

[22] 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.

[23] 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 qualtativelythe same.

Table 2: Descriptive Statistics of primary variables in first differences

	(1)		(2)	(3)	(4)
	Continuing itemizer		Continuing non-itemizer	Start itemizer	Stop itemizer
$\Delta\log P$	0.002		0.000	-0.266	0.270
	(0.094)		(0.000)	(0.100)	(0.101)
	$\Delta\log P \mid \Delta\log P > 0$	$\Delta\log P \mid \Delta\log P < 0$			
	0.047	-0.048			
	(0.069)	(0.070)			
$\Delta\log D$	0.042		0.002	0.579	-0.462
	(2.441)		(3.020)	(3.226)	(3.148)
	$\Delta\log D \mid \Delta\log P > 0$	$\Delta\log D \mid \Delta\log P < 0$			
	0.055	0.021			
	(2.447)	(2.447)			
Observations	7425		7758	2195	1846

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 income (which we control for), are almost 0 on average. However, the mean increase (35 percent of continuing itemizers experience an increase) in P for continuing itemizers is 0.047 and the mean decrease is 0.048 (45 percent of continuing itemizers experienced a decrease). Start itemizers, who necessarily face a decrease in the price and see a 0.266 fall in the 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. Stop itemizers (who necessarily face a price increase) face an average price increase of 0.270. These large price changes are driven almost entirely by the changes in itemization status. 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 donations conditional on the continuing itemizer facing a price increase is 0.055 and is statistically indistinguishable from the mean change in donations conditional on the continuing itemizer facing a decrease in price of 0.021 ($p-$value=0.600). The implied elasticity of donations for continuing itemizers is between -0.44 (for those facing an decrease in price) and 1.17 (for those facing an increase in price). For switchers the implied elasticity is -2.18 for start itemizers and -1.71 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 consistent with what we see here. We show below that this result persists when controlling for income, deductible expenses and marital status.

The marginal tax rates with which we compute the price are obtained using the National Bureau of Economic Research's Taxsim programme (Feenberg and Coutts, 1993) which 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. The marginal tax rate is a function of taxable income and therefore a function of charitable donations if the person itemizes. To address this source of endogeneity we calculate the marginal tax rates with giving set to $1 to construct the 'first-dollar price of giving' as is frequently done in the literature (e.g. Bakija and Heim, 2011; Reinstein, 2011). The correlation between the first-dollar price and the price based on marginal tax rates calculated at the actual levels of giving is 0.97.[24]

We define the marginal tax rate as

$$\tau_{it} = \left[\tau_{it}^{F} + \delta_{it}^{S}\tau_{it}^{S} - \tau_{it}^{S}\tau_{it}^{F}\delta_{it}^{F}\right] \tag{1}$$

where τ^F is the federal marginal tax rate faced by i in year t, τ^S is the state marginal tax rate, δ^S is a dummy equal to one if donations can be deducted from state returns, and δ^F is a dummy equal to one if federal taxes can be deducted from state returns and I_{it} is equal to 1 if i itemizes in year t and 0 otherwise.

3.1 Exogenous variation in $\Delta\tau$ as an instrument for $\Delta\log P$

We know by Theorem 1 that the OLS-FD estimator of β in the standard model is biased. As noted above one common solution would be to use the exogenous variation in price coming from the exogenous variation in τ. The assumption the τ is exogenous has been used throughout the literature (e.g. Abrams and Schitz, 1978; McClelland and Kokoski, 1994; Auten, Sieg and Clotfelter, 2002; Bakija and Heim, 2011). The largest changes to federal tax rates occurred in the Economic Growth and Tax Relief Reconciliation Act of 2001 and the Jobs and Growth Tax Relief Reconciliation Act of 2003. 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.

By Theorem 1 the source of bias from $\Delta\log(P_{it})$ where $P_{it} = 1 - I_{it}\tau_{it}$ arises from those who switch status, not from the change in the marginal rate of tax. We can exploit the exogenous variation in $\Delta\log(P_{it})$ using as instrument $\Delta\tau_{it}$ which has been accepted in both tax-filer and survey data as an exogenous source of price variation conditional on taxable income. As noted in Section 2 $\Delta\tau_{it}$ varies not only with the changes in tax policy discussed here but also with changes in taxable income which can result in a bias.

Once we control for a potential non-linearity in the income effect on donations, we remove the endogenous variation in both $\Delta\log(P_{it})$ and $\Delta\tau_{it}$ from income. As such the remaining variation in $\Delta\tau_{it}$ is from the exogenous changes to tax policy. We therefore consider a non-linear income generalization, including squares and cubes as is done in Bakija and Heim (2011), for the 2SLS estimator and the Itemiser model and find no appreciable difference in the results from the linear income specification

[24] The use of the first-dollar might be cause for concern about misspecification if in fact the price people respond to is the last-dollar price. Note that we have redone all our estimation in this paper using the first-dollar price as an instrument for the last-dollar price and result are nearly identical to what we present here due to the near perfect correlation between the first and last dollar prices.

that serves as our baseline. Results are provided in Appendix C.

4 Results

We present our primary results in Table 3. We estimate equation (4) 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), 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 homeownership. 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. We check the robustness of our results to the use of a Tobit estimator in Appendix C.

Table 3: Main results

	(1)	(2)	(3)	(4)
	Standard model	2SLS 1	2SLS 2	Itemizer model
$\Delta \log P$	-1.306***	-0.902	-0.804	-0.115
	(0.181)	(0.844)	(0.812)	(0.309)
Δitemizer				0.433***
				(0.099)
Observations	19342	19342	19342	19342
R^2	0.019	0.015	0.015	0.020
First stage F-test		0.000	0.000	
$H_0 : \beta_{\Delta Logprice} < -1$	0.954	0.453	0.404	0.001

Notes: Results in columns (1) are obtained from OLS-FD estimation of equation (4) for itemizers only and for the full sample respectively. Results in columns (2) and (3) are from 2SLS-FD estimation of equation (4). 2SLS 1 uses $\Delta\tau_{it}$ as the instrument and 2SLS 2 further includes the square and cube of $\Delta\tau_{it}$. Results in column (4) are from OLS-FD estimation of equation (8). All standard errors are clustered (at the household level). The penultimate row test that the 2SLS-FD estimator is identified. 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 equation (4) using the full sample so we can estimate the price elasticity for the average taxpayer. We find an estimated elasticity of -1.31 (95 percent confidence interval: -1.67 to -0.94). These results are very much in line with those surveyed in Peloza and Steel (2005) and Batina and Toshihiro (2010), for studies using both itemizers and non-itemizers (i.e. survey data). Note, however, that the estimate in column (1) suffers from the bias derived in Theorem 1.

To address the bias we re-estimate equation (4) using the full sample via 2SLS-FD. In column (2) we use $\Delta\tau_{it}$ as an instrument for $\Delta\log(P_{it})$. In column (3) we add the square and cube of $\Delta\tau_{it}$ as instruments for $\Delta\log(P_{it})$ in an attempt to increase the precision of the 2SLS-FD estimator though the standard errors remain large (95 percent confidence interval for 2SLS 2: -2.40 to 0.79).[25] In neither 2SLS 1 and 2SLS 2 do we reject the null hypothesis that $\beta = 0$ nor that $\beta \leq -1$. Though these estimates of β are consistent they both have extremely large standard errors such that 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 (8) via OLS-FD. As shown in Theorem 2 this specification will yield consistent estimates of β under the restriction that $\bar{\tau}_1 - \bar{\tau}_{-1}$. We test this restriction using the estimation sample and find $\bar{\tau}_1 - \bar{\tau}_{-1} = -0.0004$, p-value=0.873. The point estimate of the price elasticity in column (4), -0.12 (95 percent confidence interval: -0.73 to 0.50), is very close to and not significantly different from 0. However, the efficiency of the OLS-FD estimator relative to the 2SLS-FD estimator means that along with the consistent estimator of β, the standard errors are substantially smaller. In fact, the standard errors decrease nearly three times 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.[26]

As noted above, the consistency of the estimates in 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 -1.19. 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.

We run a number of robustness checks the results of which are presented in Appendix C. We estimate both the standard and itemizer models using 2SLS with first differences, using mean differenced data (both OLS and 2SLS), allowing for non-linearities in the income effect and using Correlated Random Effects Tobit. In each case results are consistent with those in Table 3.
Finally note to the large positive estimate of γ of 0.433 suggests (conditional ΔX_{it}) average log donations of start and stop itemizers relative to non-switchers is +0.433 and -0.433, 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 γ must be greater than zero and reflects the response to endogenous price changes of switchers, not a true price effect. It may be the case the price response for switchers differs to non-switchers, in this case γ may indeed pick up some true price effect, and we may overestimate the bias. Section 4.1 considers this point by considering non-linear generalizations of our model.

[25] We tried adding higher order polynomials but no further meaningful increases in precision were obtained

[26] 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.

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

While controlling for itemization status allows us to consistently estimate the price elasticity of giving, further complications arise if there are other problems with the standard specification of the donations model (equation (4)). Another key restriction of Equation (4) is that the price effect is assumed to be linear in $\Delta\log(P_{it})$ and is the same for switchers and continuous itemizers. For example if the response (*ceteris paribus*) to a 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. 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. This independent 'itemization effect' was considered early in the literature in Dye (1978). He estimates a specification 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.

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. Further to note this is also the case in the standard economic model even without a bias and is a point that has received little attention in the literature. 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 4.

Table 4: Non-linear effect of $\Delta\log(P_{it})$

	(1)	(2)	(3)	(4)	(5)
	Switchers	Quadratic	$\lvert\Delta\log P\rvert>0.15$	$\lvert\Delta\log P\rvert>0.25$	$\lvert\Delta\log P\rvert>0.36$
$\Delta\log P$	-0.046	-0.115	0.067	-0.050	-0.055
	(0.350)	(0.309)	(0.300)	(0.294)	(0.290)
Δitemizer	0.404***	0.433***	0.472***	0.452***	0.451***
	(0.150)	(0.099)	(0.092)	(0.092)	(0.091)
Switcher$\times\Delta\log P$	-0.179				
	(0.606)				
$\Delta\log P^2$		0.018			
		(0.468)			
$\Delta\log P\times 1(\lvert\Delta\log P\rvert>0.15)$			-0.169		
			(0.128)		
$\Delta\log P\times 1(\lvert\Delta\log P\rvert>0.25)$				-0.054	
				(0.149)	
$\Delta\log P\times 1(\lvert\Delta\log P\rvert>0.36)$					-0.069
					(0.176)
Observations	19342	19342	19342	19342	19342
R^2	0.020	0.020	0.018	0.017	0.017
$H_0:\beta_{\Delta \text{Log}P}\leq -1$	0.003	0.002	0.001	0.002	0.003

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 $Switcher\times\Delta\log P$ ($\hat{\rho}=-0.936$), 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 0.40 to 0.45 even when allowing for different possible non-linearities in $\Delta\log(P_{it})$. We take this stability across the specifications as evidence in support of treating γ as a nuisance parameter reflecting the bias from including switchers and not a genuine non-linearity to large changes in price that accompany changes in itemization status.

4.2 Price effects by income class

Studies using tax-filer data that omit endogenous itemizers 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. As can be seen in Table 2, itemizers are, on average, wealthier than non-itemizers and it is not obvious the degree to which the effect found in Bakija and Heim is due to those people being itemizers or higher income earners.

Some researchers (Feldstein and Taylor, 1976; Reece and Zieshang, 1985) have found 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.

We now study the tax-price elasticity over income for both the standard and the itemizer model.[27] To do this we use the bottom quintile, due to the lack of price variation among lower income earners.and then decile groups and the top ventile above that. As can be seen in Table 5, 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.

Table 5: Descriptive statistics by income

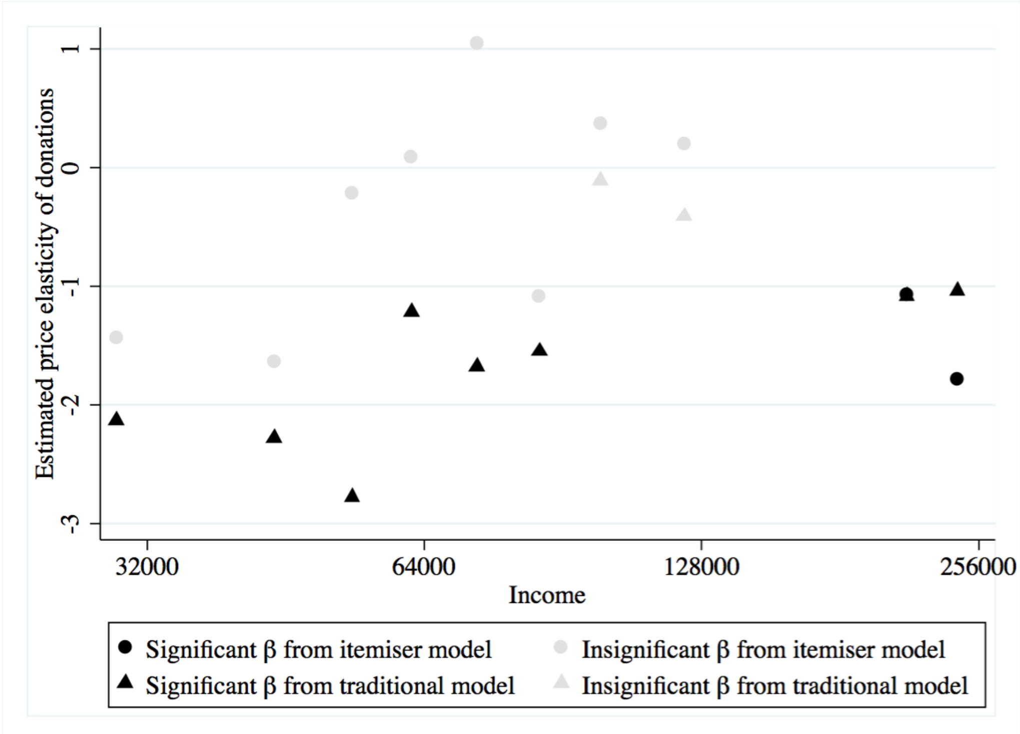
	(1)	(2)	(3)	(4)	(5)	
Group	Mean income ($'000)		P[Switcher]	P[Cont. itemizer]	Var[$\Delta\log P$]	$H_0: \bar{\tau}_1 = \bar{\tau}_{-1}$
	All	Itemizers				
1	24.065	24.530	0.106	0.038	0.006	0.200
2	34.887	35.650	0.159	0.094	0.012	0.337
3	44.001	45.471	0.200	0.149	0.014	0.555
4	53.460	53.643	0.243	0.188	0.015	0.757
5	62.018	63.323	0.261	0.279	0.019	0.415
6	73.080	75.683	0.257	0.346	0.021	0.838
7	85.405	87.656	0.263	0.448	0.026	0.153
8	99.466	103.281	0.219	0.545	0.028	0.281
9	122.759	124.623	0.195	0.634	0.030	0.444
10	214.082	219.616	0.168	0.748	0.035	0.921
95	242.733	248.430	0.169	0.765	0.035	0.530

Notes: This table presents some relevant descriptive statitcs by income decile group. These income groups form the basis of Figures 1, 2 and 3.

Figure 1 we plot the estimated price elasticities from both the standard model and the itemizer model across these income groups.

[27] To avoid losing observations that become singletons when the sub-samples are defined, we calculate the mean 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}).

Figure 1: Variation in estimated price elasticities over income



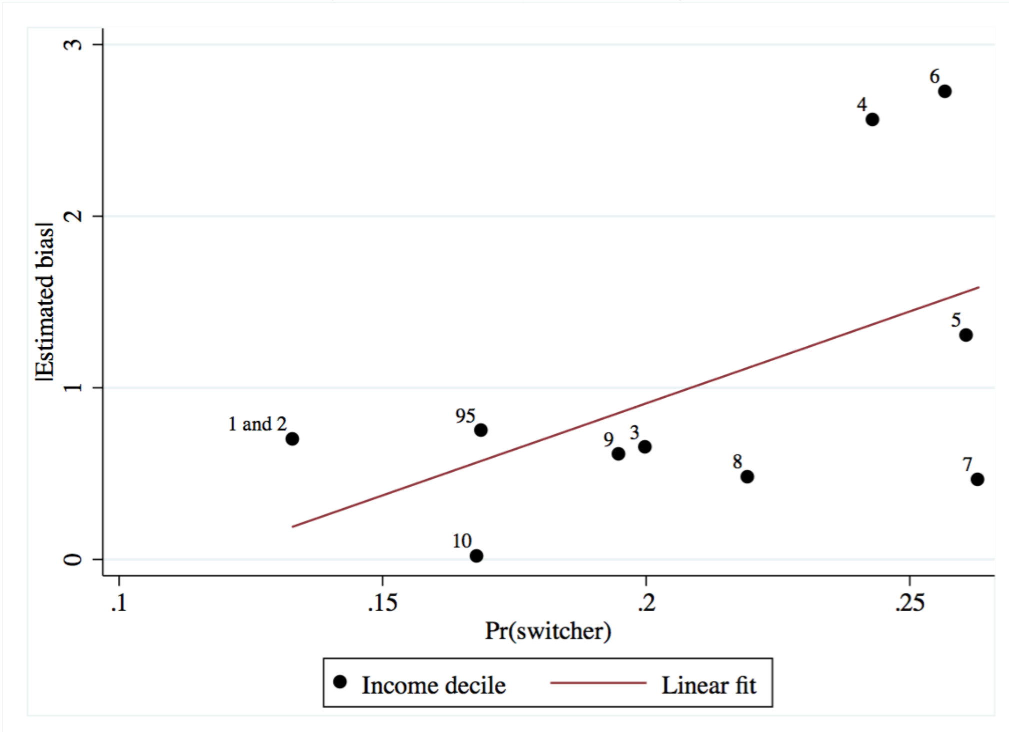
Black markers indicate a statistically significant (at the 10 percent level) estimate of β and gray markers are insignificant estimates. Estimates from the standard model are triangles and the circles are estimates from the itemizer model. With the standard model, we find the large and significant price elasticities for lower seven income deciles and for the top decile and ventile groups, though the elasticity is smallest, in absolute value, for the top ventile. These results suggest that the responsiveness of donors to changes in the price diminishes as income rises. In contrast, none of the estimates for the bottom 90 percent of the income distribution are significant. But we do find some evidence that the higher income earners are sensitive as the estimated elasticities for the top decile (p-value=0.108) and top ventile (p-value=0.025) groups are significant.[28]

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 (see the last column of Table 5, 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 higher. Below we plot the absolute size of the bias against the probability of switching within each income decile. By Theorem 1 the size of the bias increases in p_1, p_{-1} and decreases in $\text{Var}(\Delta\log P)$ for a given ξ_1, ξ_{-1} which are unobservable

[28] Note the estimates from the two models for the top decile lie right on top of one another making them potentially hard to see separately.

(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 positive (though not necessarily linear) relationship between the size of the bias and the probability of switching across income deciles.

Figure 2: Absolute Bias plotted against Probability of Switching Itemization across Income Deciles



We see some support for this in Figure 2.[29] The correlation between the probability of switching status and the size of the bias is 0.534.

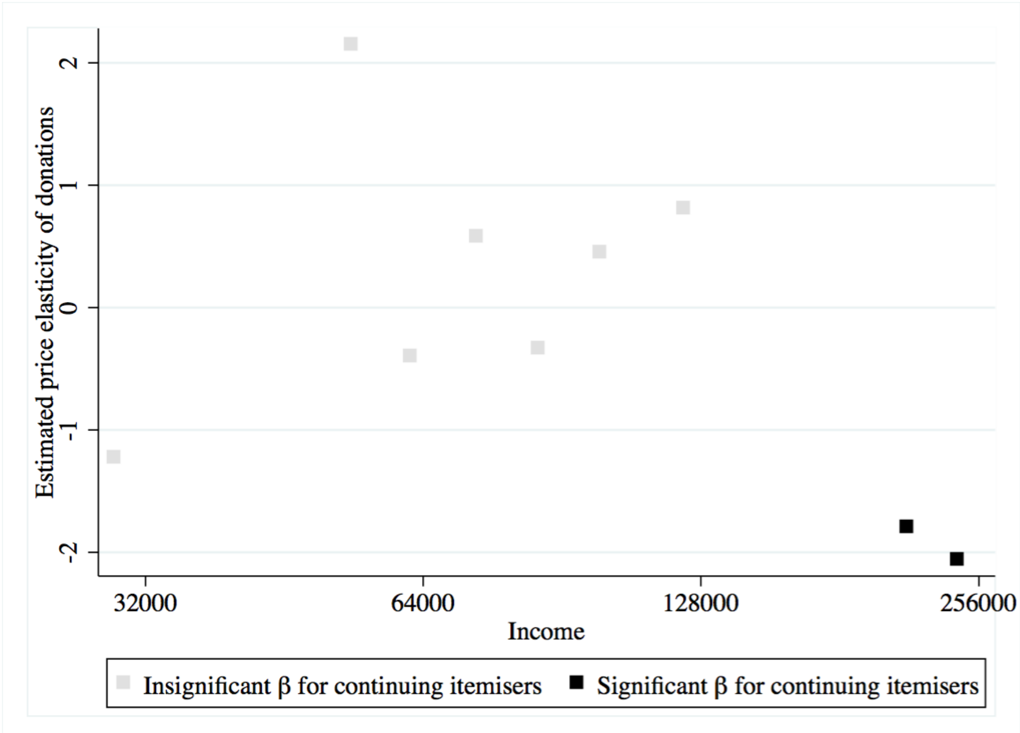
It is difficult to conceive of an economic rational for the finding in the standard model why lower income households would be more responsive to tax incentives than richer households. The results and discussion in this section utilizing Theorem 1 and 2 provide some evidence this finding is at least 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 and top ventile of earners in our data. It is clear, however, that higher income people are also more likely to itemize, as can be seen in Table 5. 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

[29] We exclude the top ventile from Figure 2 as the point estimate from the itemizer model is actually more negative than that from the standard model.

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 3.

Figure 3: Price elasticity by income group for continuing itemizers



The gray markers are insignificant (at the 10 percent level) estimates of the price elasticity for continuing itemizers and the black markers are statistically significant. Note the bottom group in the figure is actually the bottom three income deciles combined as there is such a small number of continuing itemizers at lower levels of income, as can be seen in Table 5. Note also from Table 5 that itemizers do have higher than average within decile group income, though the incomes of itemizers are qualitatively very similar to the mean income in each case.

We estimate a price elasticity of -0.27 (95 percent confidence interval: -0.992 to 0.451) for the average continuing itemizer, though note the average income of itemizers in our sample is well below that of in Bakija and Heim (2011). We do find evidence that the highest earning itemizer, those in the top decile or ventile groups, do exhibit a rather substantial sensitivity to changes in the price of giving with elasticities around -2. Itemizers at lower levels of income do not seem to be sensitive to changes in the price of giving. These results, taken together with those in Figure 1, 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 and 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 tax-price elasticity in the standard model across different income levels show the size of tax-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 removing the charitable deduction for those households below the top marginal tax bracket or revising the subsidy in line with Saez (2004).

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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 $p_1 = \mathcal{P}\{\Delta I_{it} = 1\}$, $p_{-1} = \mathcal{P}\{\Delta I_{it} = -1\}$, $p_0 = \mathcal{P}\{\Delta I_{it} = 0\}$, $\xi_1 = E[u_{it} \log(P_{it}) | \Delta I_{it} = 1]$, $\xi_{-1} = E[u_{it} \log(P_{it}) | \Delta I_{it} = -1]$. 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

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

since we control for (polynomials in) E_{it} and is uncorrelated with u_{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 the second inequality 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

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

where the second inequality follows by (9) and noting E_{it} is mean independent of u_{it} since we can control for (polynomials of) E_{it}.[30] The final inequality follows as $E[u_{it}] = 0$ (by assumption or via inclusion of a constant) then defining $p_{11} = \mathcal{P}\{u_{it} \geq h_{it}\}$

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

where $-\beta \log(1 - \tau_{it}) \leq 0$ and $-\log(S_{i,t-1} - E_{i,t-1}) \leq 0$ so that $h_{it} \leq 0$ (where the inequality holds strictly for some i,t) implies $E[u_{it}|u_{it} \leq h_{it}] < 0$ so that

$$E\left[u_{it}|u_{it} \geq h_{it}\right] > 0. \tag{14}$$

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

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

By independence of τ_{is} and u_{it}

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

where (14) and (16) imply

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

where together with the inequality in (15) implies

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

We now consider the second term in the RHS of (6) for $\Delta I_{it} = -1$. By a similar argument to the case $\Delta I_{it} = 1$

$$\begin{aligned} u_{it} &\leq \log(S_{it} - E_{it}) - \beta \log(1 - \tau_{i,t-1}) - \log(D_{i,t-1}) && (19) \\ &\leq \log(S_{it} - E_{it}) && (20) \end{aligned}$$

[30] To ease notational burden we drop the condition $E_{it} \geq S_{it}$ and similarly $E_{i,t-1} \geq S_{i,t-1}$ for $\Delta I_{it} = -1$ noting these drop out due to mean independence.

as $-\log(D_{i,t-1}) \leq 0$ and $-\beta \log(1-\tau_{i,t-1}) \leq 0$ as $\beta \leq 0$ and by a similar argument to above

$$-E[\log(1-\tau_{i,t-1})u_{it}|\Delta I_{it}=-1] = E[-\log(1-\tau_{i,t-1})|\Delta I_{it}=-1]E[u_{it}|\Delta I_{it}=-1] \tag{21}$$

$$\begin{aligned} E[u_{it}|\Delta I_{it}=-1] &\leq E[u_{it}|u_{it} \leq \log(S_{it}-E_{it})] && (22)\\ &< 0 && (23) \end{aligned}$$

using the fact $E[u_{it}]=0$ and $\log(S_{it}-E_{it}) \geq 0$ and is strictly greater then zero for some i.t. Then since $E[-\log(1-\tau_{i,t-1})] > 0$ together with the above implies

$$\xi_{-1} := -E[\log(1-\tau_{i,t-1})u_{it}|\Delta I_{it}=-1] < 0. \tag{24}$$

establishing the result.

Proof of Theorem 2

We specify our itemizer specification (Equation (4) in the text)

$$\Delta \log(D_{it}) = \gamma \Delta I_{it} + \beta \Delta \log(P_{it}) + \omega' \Delta X_{it} + e_{it} \tag{25}$$

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}

$$\Delta X_{it} = \Xi z_{it} + v_{it}^{\Delta X} \tag{26}$$

where Ξ is a $k \times 2$ matrix of OLS coefficients where by definition $E[z_{it} v_{it}^{\Delta X'}] = 0$. Plugging (26) in to (25)

$$\Delta \log(D_{it}) = \gamma^* \Delta I_{it} + \beta^* \Delta \log(P_{it}) + \omega' v_{it}^{\Delta X} + e_{it} \tag{27}$$

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 (25) and (27) that

$$\beta = \beta^* - \omega' \Xi_2 \tag{28}$$

likewise it is straightforward to show that the sample estimator satisfies

$$\hat{\beta}^{I}_{FD} = \hat{\beta}^{I,*}_{FD} - \hat{\omega}^{I,*'}_{FD} \hat{\Xi}_2 \tag{29}$$

where $\hat{\beta}^{I,*}_{FD}$, $\hat{\omega}^{I,*}_{FD}$ are the OLS estimators in (27) and $\hat{\Xi}_2$ is the estimator of Ξ_2 from OLS regression in (26). Namely we have 'partialled out' ΔX_{it}. Below we show the following two results

$$\hat{\beta}^{I,*}_{FD} \rightarrow \beta^* + \frac{p_1 p_{-1}}{C} (\bar{\tau}_1 - \bar{\tau}_{-1})(E[e_{it}|\Delta I_{it}=-1] + E[e_{it}|\Delta I_{it}=1]) \tag{30}$$

$$\hat{\omega}^{I,*}_{FD} \rightarrow \omega \tag{31}$$

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), (30) and (31) imply

$$\hat{\beta}^{I}_{FD} \xrightarrow{p} \beta + \frac{p_1 p_{-1}}{C}(\bar{\tau}_1 - \bar{\tau}_{-1})(E[e_{it}|\Delta I_{it} = -1] + E[e_{it}|\Delta I_{it} = 1]). \tag{32}$$

To show (30) and (31) define $w^*_{it} = (z'_{it}, v^{\Delta X'}_{it})'$ and the OLS estimator in (27)

$$\hat{\theta}^{I,*}_{FD} := \left(\sum_{i=1}^{N}\sum_{t=2}^{T} w^*_{it} w^{*'}_{it}\right)^{-1} \sum_{i=1}^{N}\sum_{t=2}^{T} w^*_{it}\Delta\log(D_{it}) \tag{33}$$

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

$$\begin{aligned}
\hat{\theta}^{I,*}_{FD} \quad &\xrightarrow{p} \quad E[w^*_{it} w^{*'}_{it}]^{-1} E[w^*_{it}\Delta\log(D_{it})] && (34)\\
&= \begin{pmatrix} \gamma^* \\ \beta^* \\ \omega \end{pmatrix} + \begin{pmatrix} E[z_{it}z'_{it}] & E[z_{it}v^{\Delta X'}_{it}] \\ E[v^{\Delta X}_{it} z'_{it}] & E[v^{\Delta X}_{it} v^{\Delta X'}_{it}] \end{pmatrix}^{-1} \begin{pmatrix} E[e_{it}z_{it}] \\ E[e_{it}v^{\Delta X}_{it}] \end{pmatrix} && (35)\\
&= \begin{pmatrix} \gamma^* \\ \beta^* \\ \omega \end{pmatrix} + \begin{pmatrix} E[z_{it}z'_{it}]^{-1} & 0 \\ 0 & E[v^{\Delta X}_{it} v^{\Delta X'}_{it}]^{-1} \end{pmatrix} \begin{pmatrix} E[e_{it}z_{it}] \\ 0 \end{pmatrix} && (36)
\end{aligned}$$

where (35) follows plugging in $\Delta\log(D_{it}) = \gamma^*\Delta I_{it} + \beta^*\Delta\log(P_{it}) + \omega^{'} v^{\Delta X}_{it} + e_{it}$ and (36) follows as $E[e_{it}v^{\Delta X}_{it}] = 0$ and $E[z_{it}v^{\Delta X'}_{it}] = 0$. Hence we establish (31). It follows by (35) (noting $z_{it} = (\Delta I_{it}, \Delta\log(P_{it}))$' that

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

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)

$$\begin{aligned}
\hat{\beta}^{I,*}_{FD} - \beta^* \quad &\xrightarrow{p} \quad \frac{1}{C}\left(E[e_{it}\Delta\log(P_{it})]E[(\Delta I_{it})^2] - E[\Delta I_{it}\Delta\log(P_{it})]\right)E[e_{it}\Delta I_{it}] && (37)\\
&= \frac{1}{C}((p_1 + p_{-1})E[e_{it}\Delta\log(P_{it})]) - (\bar{\tau}_1 p_1 + \bar{\tau}_{-1}p_{-1})E[e_{it}\Delta I_{it}]) && (38)\\
&= \frac{1}{C}\left((E[e_{it}\Delta\log(P_{it})] - \bar{\tau}_1 E[e_{it}\Delta I_{it}])\,p_1 + (E[e_{it}\Delta\log(P_{it})] - \bar{\tau}_{-1}E[e_{it}\Delta I_{it}])\,p_{-1}\right) && (39)\\
&= \frac{1}{C}p_1 p_{-1}(\bar{\tau}_1 - \bar{\tau}_{-1})(E[e_{it}|\Delta I_{it} = -1] + E[e_{it}|\Delta I_{it} = 1]) && (40)
\end{aligned}$$

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

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

$$\begin{aligned} E[\Delta I_{it}\Delta \log(P_{it})] &= E[\Delta \log(P_{it})|\Delta I_{it} = 1]p_1 - E[\Delta \log(P_{it})|\Delta I_{it} = -1]p_{-1} && (41) \\ &= E[\Delta \log(1-\tau_{it})|\Delta I_{it} = 1]p_1 + E[\Delta \log(1-\tau_{i,t-1})|\Delta I_{it} = -1]p_{-1} && (42) \\ &= \bar{\tau}_1 p_1 + \bar{\tau}_{-1} p_{-1} && (43) \end{aligned}$$

and the final equality (40) uses the LIE and strict exogeneity of τ_{it} so that

$$E[e_{it}\Delta \log(P_{it})] = E[e_{it}|\Delta I_{it} = 1]\bar{\tau}_1 p_1 - E[e_{it}|\Delta I_{it} = -1]\bar{\tau}_{-1} p_{-1} \tag{44}$$

$$E[e_{it}\Delta I_{it}] = E[e_{it}|\Delta I_{it} = 1]p_1 - E[e_{it}|\Delta I_{it} = -1]p_{-1} \tag{45}$$

and

$$E[e_{it}\Delta \log(P_{it})] - \bar{\tau}_1 E[e_{it}\Delta I_{it}] = (\bar{\tau}_1 - \bar{\tau}_{-1})E[e_{it}|\Delta I_{it} = -1]p_{-1} \tag{46}$$

where by a similar argument we can show

$$E[e_{it}\Delta \log(P_{it})] - \bar{\tau}_{-1} E[e_{it}\Delta I_{it}] = (\bar{\tau}_1 - \bar{\tau}_{-1})E[e_{it}|\Delta I_{it} = 1]p_1. \tag{47}$$

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)
$P = 1 - I\tau^{First}$	0.746	1.000	0.770	1.000	0.752	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	7425	7758	2195	1846	12540	13876

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.

Appendix C

Robustness checks

We carry out a number of robustness checks. First we consider the impact of using mean rather than first differencing and the exclusion of those households who never itemize, and therefore experience no price variation.

Table C.1: Robustness checks I, WG and 'never itemizers'

	(1)	(2)	(3)	(4)
	Within Group		No never itemizers	
	Standard	Itemizer	Standard	Itemizer
$\Delta\log P$	-1.465***	-0.280	-1.306***	-0.141
	(0.150)	(0.259)	(0.181)	(0.309)
Δitemizer		0.445***		0.430***
		(0.085)		(0.093)
Observations	27003	27003	19342	17882
R^2	0.038	0.040	0.019	0.021
$H_0 : \beta_{\Delta\log P} \leq -1$	0.998	0.003	0.954	0.003

Notes: 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 (4) and (8) respectively. Results in columns (3) and (4) are obtained from OLS-FD estimation of equations (4) and (8), respectively, excluding those households who never itemize during the observed period. For these households the price is always equal to 1, so there is no variation in price. In each case 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 by including squares and cubes of log income as additional regressors. Results, presented in Table 3, replicate those in Table 3 and do not qualitatively differ.

Table C.2: Robustness checks II, allowing for a non-linear income effect

	(1)	(2)	(3)	(4)
	Standard model	2SLS 1	2SLS 2	Itemizer model
$\Delta\log P$	-1.313***	-0.741	-0.656	-0.120
	(0.183)	(0.838)	(0.811)	(0.312)
Δitemizer				0.432***
				(0.100)
Observations	19342	19342	19342	19342
R^2	0.019	0.015	0.015	0.021
First stage F-test		0.000	0.000	
$H_0 : \beta_{\Delta Logprice} < -1$	0.965	0.379	0.364	0.002

Notes: 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%.

We also test the robustness of our result 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 (Mundlak, 1978) Tobit estimator where the within household time means of each time varying regressor are included as additional regressors. Estimated effects on the conditional (on $D > 0$) means (intensive margin) are presented in Table C.3.

Table C.3: Robustness checks III, Tobits

	(1)	(2)
	Standard	Itemizer
$\Delta\log P$	-1.128***	-0.019
	(0.134)	(0.223)
Δitemizer		0.422***
		(0.075)
Observations	27003	27003
$H_0 : \beta_{\Delta\log P} \leq -1$	0.340	0.000

Notes: 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%.

Our result maintains. The standard specification produces statistically significant estimated price elasticities around -1. Our specification again returns estimated elasticities very close to, and not statistically different from, 0 and different from -1 from the itemizer model.

Dear Editor,

Enclosed is a copy of our paper *"Consistent Inference of the Tax-Price Elasticity of Charitable Giving with Survey Data"* for consideration to be published in the Journal of Public Economics.

We consider methods to consistently estimate the tax-price elasticity of charitable giving with respect to price using US Survey Data. A number of papers estimating this elasticity on Survey Data have found unrealistically large price elasticities, with some papers finding the unusual result that the price response is largest for the lowest income households.

Overall this paper provides an explanation for these findings, showing formally they arise from a bias in the standard model arising from agents switching tax itemisation status.

To address this bias we consider an IV approach (using as instrument for the change in the price the exogenous changes in the marginal tax rate). Though identified, the standard errors are far too large to make any meaningful economic inference.

In light of this we use the fact that the source of the endogeneity is known- arising from those who switch status, which we can measure. We derive the asymptotic bias in the OLS-FD estimator in a model which controls for change in itemisation status. This bias is zero under a testable restriction which we find very strong evidence for throughout the paper and the generalisations we consider. The benefit of this approach is that is exploits the maximal amount of exogenous variation in the price and is estimated via OLS and yields standard errors almost $1/3^{rd}$ of those found with the IV estimator.

Using this model we find evidence, unlike many of the findings in the literature using survey data, that the average taxpayer has an inelastic price response. We find it is the higher income households (top 10%) displaying a strong response to price, with evidence the lower 90% are unresponsive to price.

Yours faithfully,

Nicky Grant & Peter Backus, June 16 2016.