Bias in Estimating the Tax-Price Elasticity of Charitable Donations on Survey Data

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Abstract

This paper addresses the empirical puzzle where the tax-price elasticity of charitable donations estimated on survey data is generally larger than that found on tax-filer data which over-samples wealthier individuals. We provide theoretical and empirical evidence that this finding is due to a downward bias in the estimator of the tax-price elasticity in the economic model for charitable donations on survey data where non-itemisers are included in the sample. An intuitive modification to this model is provided which is shown to yield a consistent estimator of the tax-price elasticity under a simple testable restriction on the conditional marginal tax rates in different sub-populations. We find strong empirical verification that this restriction holds and estimate a bias in the tax price elasticity in the baseline model around -1. This bias explains both the unusual empirical finding of a strong elastic tax-price response on general population survey data and that this elasticity is of a larger magnitude than that estimated on tax-filer data. Only for those individuals with income in the top 5% decile is a statistically significant tax-price elasticity found of a magnitude consistent with those estimated on tax-filer data.

Keywords: charitable giving, tax incentives

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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), "The Economics of Giving"

The response to tax incentives for charitable giving, particularly in the US, have been well studied in the economics literature dating back to at least the work of Tausing (1967). In the US, taxpayers can deduct their charitable donations from their taxable income if they choose to itemise, or list, their deductible expenditures (e.g. donations, mortgage interest payments) in their annual filing. The deductibility of donations produces a price of donating one dollar of one minus the marginal tax rate faced by the donor should she itemise her tax return and equal to one otherwise.

Broadly speaking this literature has estimated the tax-price elasticity of charitable donations using tax-filer data and survey. Tax filer data contains donations information only for those people who itemise their tax returns and non-itemisers are generally excluded from the analysis. As such, identification of the tax-price elasticity is based on changes in the price coming from arguably exogenous changes in the marginal tax rates. Studies using survey data contain both itemisers and non-itemisers and can exploit variation prices from variation in both the marginal tax rate and itemisation status. While both data sources have advantages and disadvantages, a perhaps puzzling finding is that the price elasticity of donations estimated from survey data tends to be of a larger magnitude than that estimated from tax-filer data. This finding is somewhat surprising as we would expect the elasticity in the survey data sampling from the general population to be no larger than that of the wealthier more well informed individuals in tax-filer data.

In this paper we revisit the estimation of the price elasticity of charitable donations and show that estimated price elasticities identified using changes in itemisation status will be severely biased. We provide strong theoretical and empirical evidence that this finding is largely due to a downward bias in the estimator of the elasticity in the current economic model on survey data.

A straightforward extension to this model is provided which yields a consistent estimate of the tax-price elasticity under a simple testable restriction. This restriction is strongly supported by the data where we find evidence in this model of an inelastic tax-price response which is statistically indistinguishable from zero in the general population. Only for those with income in the top 10% decile is a statistically significant and elastic price response observed, consistent with the findings in tax-filer data. This provides one explanation for the hypothesis of Clotfelter (2002) and others that the current estimates of the responsiveness of charitable giving to tax incentives in the general population are unrealistic. This finding is also significant for public policy analysis as a tax price elasticity less than unity is indicative that the tax deductibility of charitable donations may not be 'treasury efficient.[1]

To see why the itemisation status is important note that the decision to itemise or not can be determined by the level of donations. This fact results in a long recognised source of endogeneity caused by so-called 'endogenous itemisers', i.e. people who would not have itemised in the absence of donations. The conventional approach to mitigate the bias generated by this endogeneity has been to drop the 'endogenous itemisers' observations from the estimation sample (e.g. Clotfelter 1980, Randolph, 1995; Bakija and Heim, 2011). Such an exclusion is fairly innocuous as endogenous itemisers tend to make up a rather small proportion of samples. There is, however, a corresponding problem that has not yet been addressed in the literature; Endogneous Non-itemisers. That is, just as endogeneity is introduced by including donors who itemise but would not have in the absence of donations, there is endogeneity in the decision not to itemise as there is an upper bound on donations for these people.

The intuition for the bias is clear in the cross sectional setting. Donations for itemisers are unbounded whereas donations for non-itemisers face an upper bound of the standard deduction minus other deductible expenditures. This upper bound on non-itemisers' donations alone can produce to a large difference between mean donations. Using data from 1986, Duquette (1999) find mean donations for non-itemisers to be $388 compared to $1463 for itemisers. This difference is certainly in part due to differences in observable characteristics like income, but it should be clear that it is likely also to be an artifact of the definition non-itemisers since non-itemisers cannot have donations larger that their other itemisable expenditures minus the

[1] Tax deductibility of chartiable 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.)

standard deduction. With panel data this difference would be picked up in the fixed effects for those people who either always itemise or never itemise. In practice, however, there are also people who itemise in some years and not in others. As such simply controlling for individual effects would not capture the difference imposed by itemisation status for these people.

For example when an agent does not itemise at time *t-1* but does at time t then the change in donation at time t is bounded above by the difference in their standard deduction and other tax deductible expenditures at *t-1*. Conditional on this type of behaviour in two adjacent periods the distribution of the change in donation (and hence the residuals in this regression) is skewed greatly to the left (negative change) where the price has increased by the marginal rate of tax (mtr) paid on the last dollar of donation last period. We show that this will lead to a negative correlation between change in price and change in donation, even if agents do not respond to tax incentives (or indeed any other variables) at all. A similar argument holds in reverse for those who itemise at time t and did not at *t-1*. For those who itemise both periods they drop out of the bias assuming changes in mtr are exogenous as there is no bound on donations either way for exogenous itemisers.[2] For those who do not itemise both periods there is no change in price and hence they also drop out of the asymptotic bias.

To overcome the issue that those who change itemisation status (either start itemising or stop itemising) will have respectively a lower or higher change in donations conditional on the mtr (and all other factors) we propose a model that controls for change in itemisation status. This simple model accommodates such a difference in the average change of donation conditional on all other factors implied by this bound to allow the identification of the true price effect. We show how the first difference estimator in this model leads to consistent estimator of the tax price effect under the testable restriction that the average change in price for stop and start itemisers are of the same magnitude. Intuitively controlling for change in itemisation status removes the variation in price arising from change in itemisation status such that we exploit only exogenous price variation from changes in mtr. As such the estimates of the tax-price elasticity in this paper based on the general population are analogous to those found on tax filer data on wealthier individuals who itemise and which by design does not suffer from the bias discussed here.

[2] The assumption that changes in mtr are exogenous is not required to show a negative bias, however is maintained for simplicity as this condition is a cornerstone for meaningul estimation of the tax-price elasticity in any model. If changes in mtr were endogenous the negative bias would be compounded even further.

The paper proceeds as follows. Section 2 provides formal theoretical results showing the downward bias in estimating the tax price response on survey data in the standard economic model. An alternative model is provided and the asymptotic bias is derived which is shown to be zero under a testable restriction. Section 3 discusses and summarises the data and Section 4 presents the main empirical results. Finally conclusions are drawn in Section 5. Proofs of the theoretical results along with extra empirical output is provided in an appendix.

2 Estimating Price Elasticities of Donation on Survey Data

The baseline economic model for donations in the literature is

$$\log(D_{it}) = \alpha_i + \beta \log(P_{it}) + \omega' X_{it} + e_{it} \tag{2.1}$$

where $D_{it} = D^*_{it} + 1$ where D^*_{it} is the level of donations for household i at time t, $I_{it} = 1(D_{it} + E_{it} > S_{it})$ is a dummy equal to 1 if i itemises at time t where $S_{it} = S^*_{it} + 1$ where S^*_{it} is the standard deduction and E_{it} is all other tax deductible expenditure, $P_{it} = 1 - I_{it}\tau_{it}$ is the price of donating a dollar where τ_{it} is the marginal rate and X_{it} is a vector of personal characteristics including income and wealth and α_i is all time invariant unobserved heterogeneity.

The parameter of interest is β, the elasticity of donations with respect to the price P_{it}. This economic model is estimated on both tax filer (e.g. Randolph, 1995; Auten, Sieg and Clotfelter, 2002; Bakija and Haim, 2011) and survey data (e.g. Bradely, Holden and McClelland, 2005; Yörük, 2010) using Within Group type estimators where panel data are available. Tax filer data uses individual tax return data which includes detailed information on income, marginal tax rates and donations, though only for those who itemise their tax returns. One survey of the literature (Peloza and Steel, 2005) found that more than half of the studies surveyed used tax filer data. Identification of the price elasticity is based on arguably exogenous changes in the marginal tax schedule. A drawback to using tax filer data is that itemisers are not representative of the population as a whole as they generally have higher average income, which is observed in tax filer data. Bakija and Heim (2011), for example, use a large panel of tax filers and their sample has a mean income of about $1 million (though they over-sample the very wealthy) and the mean income in Randolph (1995), also using tax filer data, is nearly half a million dollars. As such, these studies can potentially reveal something about the responsiveness of the relatively wealthy to changes in the price of giving but those results may not be generalisable to the wider population. Peloza and Steel report that, on average, studies using tax filer data found a price elasticity of -1.08 and in another study by Batina and Toshihiro (2005) was found to be -1.25.

Survey data, on the other hand, allows researchers to study the effect of the tax incentive for giving using a representative sample of the population and to observe donations even for those people who do not itemise their tax returns. Moreover, relevant variables such as age, education and wealth, generally unavailable in tax filer data, are usually available in survey data, providing a more complete set of controls.. Marginal tax rates generally need to be estimated as a function of available information in the survey, which may not include certain relevant variables such as deductible expenditures or itemisation status. Identification of the price elasticity in these studies is based on both changes in the marginal tax rate, τ, and changes in itemisation status, I. Peloza and Steel report that studies using survey data find a price elasticity of, on average, -1.29 (-1.62 in Batina and Toshihiro) and is significantly larger than that found in the average tax-filer study.[3] Using the same data source we do Yoruk (2010) finds price elasticities ranging from -0.73 to -2.72 and Reinstein (2011), also using the same data source as us, finds elasticities generally in excess of -1.

We now move on to discuss itemisation behaviour, especially changes over time, and how exploiting such price variation leads to a downward bias in within group type estimators.

2.1 Downward Bias in the Standard Economic Model on Survey Data

When modelling price elasticities the following three types of itemisation behaviour are important. At any time people are either exogenous itemisers ($I_{it} = 1$ where $E_{it} > S^*_{it}$), endogenous itemisers ($I_{it} = 1$ where $D_{it} + E_{it} > S_{it}$ and $E_{it} \leq S^*_{it}$) or non-itemisers ($I_{it} = 0$, i.e $D_{it} + E_{it} \leq S_{it}$).

Endogenous itemisers are people that, conditional on a given expenditure, are itemisers only because of their donation. As such the price for these agents is implicitly a function of their donation and hence causes a potentially considerable bias. One solution to this issue in the literature has been to omit endogenous itemisers (generally a small proportion of the

[3] Other recent studies have found elasticities closer to 0 than the US studies, though these studies use data from other countries (e.g. Fack and Landais (2010) use data from France, Bonke et al. (2013) use data from Germany, Scharf and Smith (2010) use UK data) with differently structured tax incentives for giving. We focus our attention on studies from the US.

observations), exploiting variation in price over time based solely on non-itemisers and exogenous itemisers.

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 itemisers. Namely $I_{it} = 0$ (non-itemiser) if $D_{it} \leq S_{it} - E_{it}$ so that a non-itemiser has donations bounded above and faces a higher price than an itemiser. This is the other side of the endogenous itemiser problem who have donations bounded below ($D_{it} > S_{it} - E_{it}$) and face a lower price relative to non-itemisers (as the mtr is greater then zero). We argue that even when omitting endogenous itemisers a large bias remains as a result of non-itemisers and that this bias is not expunged by the inclusion of individual fixed effects.

To show this formally we consider a model where endogenous itemisers are omitted and individual effects (α_i) are removed via first differencing (FD).[4] We omit endogenous itemisers to show the bias remains even removing endogenous variation as is recognised in the literature.[5] First differencing equation (2.1) gives

$$\Delta \log(D_{it}) = \beta \Delta \log(P_{it}) + \omega' \Delta X_{it} + u_{it} \tag{2.2}$$

where $u_{it} = \Delta \epsilon_{it}$. We define the following for any i, t.

I1 **Continuing Itemiser** ($\Delta I_{it} = 0$) $I_{it} = 1$, $I_{i,t-1} = 1$

I2 **Stop Itemiser** ($\Delta I_{it} = -1$) $I_{it} = 0$, $I_{i,t-1} = -1$

I3 **Start Itemiser**:($\Delta I_{it} = 1$) $I_{it} = 1$, $I_{i,t-1} = 0$

I4 **Continuing Non-Itemiser** ($\Delta I_{it} = 0$) $I_{it} = 0$, $I_{i,t-1} = 0$

where the asymptotic bias of the OLS-FD estimator in equation (2.1) depend on these 4 types of dynamic itemisation behaviour. Note we refer to stop and start itemisers jointly as switchers.

There are three sources of variation in price: 1) changes in taxable income (which we control for), 2) the exogenous variation in the marginal tax rate schedule and 3) changes in itemisation status I_{it}. Consider the case of start itemisers so $\Delta I_{it} = 1$ then $I_{it} = 1$ (i.e $E_{it} \geq S^*_{it}$ as we consider only exogenous itemisers) and $I_{it} = 0$ (i.e $D_{i,t-1} \leq S_{i,t-1} - E_{i,t-1}$). Hence $\log(D_{i,t-1}) \leq$

[4] 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.

[5] A similar result could be found including all types of itemisers but is omitted for brevity.

$\log(S_{i,t-1} - E_{i,t-1})$ where there is no bound on D_{it} by definition.[6] Hence it follows

$$\Delta I_{it} = 1 \Rightarrow \Delta \log(D_{it}) \geq \log(D_{it}) - \log(S_{i,t-1} - E_{i,t-1}) \quad (2.3)$$

$$\geq -\log(S_{i,t-1} - E_{i,t-1}) \quad (2.4)$$

as $\log(D_{it}) \geq 0$ and hence $\Delta \log(D_{it})$ is bounded below.

When $D_{it} > S_{i,t-1} - E_{i,t-1}$ then $\Delta \log(D_{it}) > 0$ so for those whose donation at time t exceeds the standard deduction net of expenses at time $t-1$ will by construction have an increase in donations. Given that $\Delta I_{it} = 1$, we know $\Delta \log(P_{it}) < 0$ and when $D_{it} > S_{i,t-1} - E_{i,t-1}$ then $\Delta \log(D_{it}) > 0$ and as such a negative correlation between price and donations will be found irrespective of the responsive of donations to price. Namely when $\mathcal{P}\{D_{it} > S_{i,t-1} - E_{i,t-1} | \Delta I_{it} = 1\} > 0$ there must be a negative correlation between change in price and change in donation, where this condition holds irrespective of β. In fact D_{it} could be picked entirely at random and, for any realistic distribution of (D_{it}, E_{it}), $\mathcal{P}\{D_{it} > S_{i,t-1} - E_{i,t-1} | \Delta I_{it} = 1\} > 0$. We find in our sample (discussed in detail below) that $\mathcal{P}\{D_{it} > S_{i,t-1} - E_{i,t-1} | \Delta I_{it} = 1\} = 0.50$.

This negative correlation between $\Delta \log(P_{it})$ and $\Delta \log(D_{it})$ introduced by start itemisers is found similarly for stop itemsiers, i.e $\Delta I_{it} = -1$. By similar reasoning as above

$$\Delta I_{it} = -1 \Rightarrow \Delta \log(D_{it}) \leq \log(S_{it} - E_{it}) - \log(D_{i,t-1}) \quad (2.5)$$

$$\leq \log(S_{it} - E_{it}) \quad (2.6)$$

so that when a person stops itemising they face a higher price and the change in donations is bounded above which leads to a negative correlation between changes in price and changes in donation. We find in the sample that $\mathcal{P}\{D_{i,t-1} > S_{it} - E_{it} | \Delta I_{it} = -1\}$ is 0.57.

Hence changes in itemisation status lead to a change in price and donations by construction irrespective of the size of the true response of the donor.[7]

Define $V_{it} = S_{it} - E_{it}$ which is one plus the standard deduction minus expenses. So $V_{it} \geq 1$ when $I_{it} = 0$ and $V_{it} < 1$ when $I_{it} = 1$. Table 1 summarises the discussion above and is useful

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

[7] When $\Delta I_{it} = 0$ then either they were exogenous itemisers both periods (as we omit endogenous itemisers) and hence there is no bound on donations in either period and τ_{it} is exogenous. If they did not itemise both periods then D_{it} and $D_{i,t-1}$ then $\Delta \log(P_{it}) = 0$.

in proving Theorem 1 below.

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

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

To derive the bias of OLS-FD in equation (2.2) in Theorem 1 we break the correlation in u_{it} and $\Delta\log(P_{it})$ into four parts corresponding to each quadrant above by the Law of Iterated Expectations. When $\Delta I_{it}=1$ (bottom left quadrant) then $\Delta\log(D_{it})$ (and hence u_{it}) are bounded below and the change in price is negative which we show leads to a negative correlation between the two variables. Conversely when $\Delta I_{it}=-1$ (top right quadrant) then $\Delta\log(D_{it})$ (and hence u_{it}) are bounded above and the change in price is positive which also leads to a negative correlation. For continuing non-itemsers (bottom right quadrant) the change in price equals zero and hence drops out of the bias, likewise for continuing itemisers (top right) there is no bound on $\log(D_{it})$ and since u_{it} is exogenous and uncorrelated with $\Delta\log(1-\tau_{it})$ this again drops out.

Theorem 1 shows the OLS-FD estimator of β in (2.2) is downward biased when proportion of individuals switch itemisation status. For simplicity to highlight the result we impose $\omega=0$.[8] Equation (2.2) then collapses to

$$\Delta\log(D_{it})=\beta\Delta\log(P_{it})+u_{it} \tag{2.7}$$

and the OLS-FD estimator of β in (2.7) is $\hat{\beta}_{FD}=\frac{\sum_{i=1}^{N}\sum_{t=2}^{T}\Delta\log(D_{it})\Delta\log(P_{it})}{\sum_{i=1}^{N}\sum_{t=2}^{T}\Delta\log(P_{it})^2}$.[9]

Theorem 1 below derives the probability limit of $\hat{\beta}_{FD}$ where we assume that $(D_{it},\tau_{it},u_{it})$ are i.i.d and that $\tau_{i,t}$ is strictly exogenous.[10] The assumption τ_{it} is exogenous is made for simplicity

[8] 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.

[9] In practise a constant would be included in (2.7) 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.

[10] 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.

to highlight the result and is relatively innocuous as u_{it} removes all time invariant heterogeneity and after we control for income and other characteristics τ_{it} is arguably exogenous.[11]

Define $p_1 = \mathcal{P}\{\Delta I_{it} = 1\}$, $p_{-1} = \mathcal{P}\{\Delta I_{it} = -1\}$.

THEOREM 1 $\hat{\beta}_{FD} \xrightarrow{p} \beta + \xi$ where $\xi = \frac{E[u_{it}\Delta\log(P_{it})]}{E[(\Delta\log(P_{it}))^2]}$ where $\xi < 0$ if $p_1 > 0$ and/or $p_{-1} > 0$.

This result can be generalised 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 itemisation status are endogenous. Note that the asymptotic bias ξ could be large in practice if the variation in tax rates is small.

A similar result could be shown for Within Group (WG) estimation where the data is mean differenced. The deviation of donations at time t from average donation over time is again bounded above when a person itemises at time t whereas no restriction is placed on this change when an agent does not itemise. Again this drives correlation between change in donation and change in price. Showing properties of WG is more involved as we need to take in to account dynamic itemisation behaviour at all time periods, not just t and $t-1$ as for FD. However a similar intuition holds to the FD case and the price variation from variation in itemisation status is inherently endogenous.

We next show how controlling for itemisation status in (2.2) can remove (or at least reduce) the asymptotic bias in the estimate of β. Intuitively including itemisation status as an additional regressor removes the variation in price coming from change in itemisation status. As such we exploit exogenous changes in the marginal tax rate as is done in Tax-Filer data where this is the only source of price variation. Theorem 2 derives the bias in the OLS-FD estimator in the Itemiser Specification which controls for ΔI_{it}, defined as

$$\Delta\log(D_{it}) = \gamma\Delta I_{it} + \beta\Delta\log(P_{it}) + \omega'\Delta X_{it} + e_{it} \tag{2.8}$$

where $u_{it} = e_{it} + \gamma\Delta I_{it}$ and $\gamma > 0$.

Define $z_{it} = (\Delta I_{it}, \Delta\log(P_{it}))'$ and $w_{it} = (z'_{it}, X'_{it})'$ the OLS-FD estimator in the Itemiser

[11] We consider also the case using the tax on the first dollar of donation as an instrument for the tax on the last dollar so that the argument would go through using the instrument in place of the tax on the final dollar.

specification

$$\hat{\theta}^I_{FD} = \left(\sum_{i=1}^{N}\sum_{t=2}^{T} w_{it}w'_{it}\right)^{-1} \sum_{i=1}^{N}\sum_{t=2}^{T} w_{it}\Delta\log(D_{it}) \tag{2.9}$$

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}).

THEOREM 2 If $E[e_{it}X_{it}] = 0$ (exogenous controls) and/or $E[z_{it}X'_{it}] = 0$

$$\hat{\beta}^I_{FD} \xrightarrow{p} \beta + \frac{p_1 p_{-1}}{C}(\bar{\tau}_1 - \bar{\tau}_{-1})(E[e_{it}|\Delta I_{it} = -1] + E[e_{it}|\Delta I_{it} = 1]) \tag{2.10}$$

Both $E[e_{it}|\Delta I_{it} = 1]$ and $E[e_{it}|\Delta I_{it} = -1]$ are likely to be close to, if not equal to, zero since $E[e_{it}] = 0$. If $E[e_{it}|\Delta I_{it} = 0] = 0$ then this condition implies

$$E[e_{it}|\Delta I_{it} = 1] = -p_1/p_{-1}E[e_{it}|\Delta I_{it} = -1] \tag{2.11}$$

so the sum $E[e_{it}|\Delta I_{it} = -1] + E[e_{it}|\Delta I_{it} = 1]$ should balance close to zero and the asymptotic bias in $\hat{\beta}^I_{FD}$ is likely to be smaller than that in $\hat{\beta}_{FD}$.
While the condition that $E[e_{it}|\Delta I_{it} = 1] + E[e_{it}|\Delta I_{it} = -1] = 0$ is not testable, by Theorem 2 there is no asymptotic bias in $\hat{\beta}^I_{FD}$ when $\bar{\tau}_{-1} = \bar{\tau}_1$. This restriction is testable and we find evidence for this empirically (discussed below). Moreover, if $\bar{\tau}_1 = \bar{\tau}_{-1}$ then Theorems 1 and 2 imply $\hat{\beta}_{FD} - \hat{\beta}^I_{FD} \xrightarrow{p} \xi$ and so that the asymptotic bias in the literature model is consistently estimable.

2.2 Interpretation of 'Itemiser Specification'

Theorem 2 shows how we can remove the negative bias in OLS-FD estimates of β from the traditional economic model under a testable restriction. The coefficient γ in the Itemiser Specification (2.8) which allows the mean change in donations for start and stop itemisers (conditional on a given mtr 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 in the standard model. Once this intercept shift is controlled for we can consistently estimate the price effect β.

However, further complications arise if there are potential problems with the traditional economic model in (2.2) beyond not allowing for the Switcher's intercept shift. Another key restriction of (2.2) is that the price effect is linear in the price change and is the same for switchers and continuous itemisers. If the price response is non-linear in the size of ΔP, for example if the response (*ceterus 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 'mop up' the differential implied by the bound and another part will pick up a genuine price response.[12]

As such we must be careful how we interpret γ and β in the presence of omitted non-linearities. If for example there is a much larger donation response to big price changes and this isn't controlled for then the intercept γ will part pick up this effect and the interpretation on β reflects roughly the effect of a 1% price change around the average level of change in price. This issue on the interpretation of β is also faced in the standard economic model with omitted non-linearities even without a bias and is a point that has not, to our knowledge, been addressed in the literature.

We consider these issues in the empirical analysis that follows. Even allowing for general flexible forms of non-linearities the bias is still found and a large intercept shift for switchers is present. We include these results to show this intercept shift is not due to a larger price response for switchers.

3 Data

We use data from the Panel Study of Income Dynamics (PSID), a bi-annual survey of American households. The focus of the PSID is economic and demographic, 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

[12] As 30% is roughly them magnitude of a price change of a switcher and 3% roughly the mean of a price change for an always itemiser (i.e roughly the average magnitude of a change in mtr).

(COPPS) module containing questions on giving and volunteering.[13]

We use seven waves of the PSID covering 2000-2012 giving us a raw sample with 58,993 observations. 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 in three or fewer years during the observed period. These restrictions leave us with a working sample of 27,152 observations (5,845 households appearing for an average of 5.4 years).

In Table 2 we present descriptive statistics for the variables used in our study for the four types of itemisers defined in Section. The unit of analysis is the household. All monetary figures are in 2014 prices.[14] Descriptive statistics for the full set of variables used in this study are available in the Appendix.

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[13] Wilhelm (2006) compares the COPPS data to tax return data in the number of missing values and the' amounts being reported and finds that the PSID survey data is of 'high quality'.

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

Table 2: Descriptive Statistics of primary variables

	Continuing itemiser	Continuing non-itemiser	Start itemiser	Stop itemiser
In levels				
Donate^d	0.892	0.488	0.727	0.670
	(0.310)	(0.500)	(0.446)	(0.470)
Total donation ($'000)	3.063	0.573	1.379	1.302
	(5.063)	(1.451)	(2.593)	(2.928)
Price	0.743	1.000	0.770	1.000
	(0.083)	(0.000)	(0.076)	(0.000)
Net taxable income ($'000)	118.463	52.177	82.796	80.208
	(149.792)	(37.126)	(68.314)	(68.858)
In differences				
ΔDonate^d	0.002	-0.003	0.073	-0.070
	(0.348)	(0.514)	(0.503)	(0.497)
Δlog total donation	0.040	0.002	0.583	-0.474
	(2.407)	(3.020)	(3.220)	(3.139)
Δ log Price	0.002	0.000	-0.266	0.271
	(0.094)	(0.000)	(0.101)	(0.101)
Δlog net taxable income	0.005	0.048	0.100	-0.052
	(0.378)	(0.400)	(0.409)	(0.470)
hline Observations	8193	7758	2236	1877

Notes: Variables with ^{d} are 0/1 dummies. All monetary figures are in 2014 prices, deflated using the Consumer Price Index. We show the first differences to three decimal places as many values are very small.

Donation behaviour varies over the itemiser types. Continuing itemisers are the most likely to donate something and give the highest donation on average, nearly four times that of continuing non-itemisers and more than double the mean donations of start and stop itemisers. Continuing itemisers also have the highest mean income and lowest mean price. The donating probability, mean donation and mean income of the start and stop itemisers are quite similar. However, key variation emerges whhen we look at the first differences. Changes in donations for continuing itemisers and non-itemisers is relatively small. For the start and stop itemisers, we see large changes on the order of 50 to 60 percent. Note these people also face relatively large changes in income and in price, driven mainly by the change in itemisation status.

Itemisation status is an important feature of our study. Actual itemisation status is reported in the survey. But we also predict itemisation status by comparing 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).[15] Self-reporting itemisers make up 48 percent of the sample. Our predicted itemisation status gives an itemisation rate of 53 percent and matches the declared itemisation status in 78 percent of the cases. Our 'over-prediction' of itemisation status is consistent with findings in Benzarti (2015) who shows that taxpayers systematically forego the savings they might accrue from itemising in order to avoid the hassle of itemising. We therefore do not define households as itemisers of any kind unless they have declared themselves as such in the survey. We define endogenous itemisers as those households who report itemising and are predicted to itemise, but only when donations are included among the itemised deductions, i.e. $(0 < S - E < D)$. Endogenous itemisers make up 3 percent of the sample. Exogenous itemisers are those households who report itemising and are predicted to itemise even in the absence on donations, i.e. $(E > S)$. Exogenous itemisers make up 45 percent of the sample and 94 percent of the itemisers.[16]

Marginal tax rates are computed using the National Bureau of Economic Research's (NBER) 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. We compute the marginal tax rates that compose the price in two ways. First, we use the reported donations to calculate to get τ^{Last}, the marginal tax rate at the last dollar of giving. This definition of the marginal tax rate will be endogenous since τ^{Last} is a function of taxable income, and therefore of donations, since taxable income can be reduced by the amount donated when donors itemise. This source of endogeneity is generally addressed by using the marginal tax rates calculated with \$1 dollar of giving, which is what we do to obtain τ^{First}, the marginal tax rate at the first dollar of giving. We use τ^{First} as both an instrument for τ^{Last} and as a proxy (in a reduced form model) as is frequently done in the literature. The

[15] In practice, 95 percent of married households file jointly. We do not observe whether those married households in our sample file jointly so we assume all married household file jointly.

[16] There is a smaller share of the sample (6.5 percent) who report themselves as itemisers but for whom we fail to predict them as such. We include these households as exogenous itemisers and test the robustness of our results to their exclusion given the uncertainty about endogenous vs. exogenous itemiser status.

correlation between τ^{Last} and τ^{First} is 0.90. We define the marginal tax rate as

$$\tau_{it}^{h} = \left[\tau_{it}^{F,h} + \delta_{it}^{S}\tau_{it}^{S,h} - \tau_{it}^{S,h}\tau_{it}^{F,h}\delta_{it}^{F}\right] \tag{3.12}$$

where $h \in \{f, l\}$ is used to denote the marginal tax rate calculated at the first (f) and last (l) dollar of giving, 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 itemises in year t and 0 otherwise. The price of giving faced by each household is therefore

$$P_{it}^{h} = 1 - I_{it}\tau_{it}^{h} \tag{3.13}$$

The key to identifying the price effect is exogenous variation in the marginal tax rates faced by household. A number of papers (Abrams and Schitz 1978; McClelland and Kokoski 1994 Randolph 1995, Auten et al. 2002, Bakija and Heim, 2011) use exogenous changes to the federal and/or state income tax schedule and we also exploit exogenous variation in state and federal marginal tax rates between 2000 and 2012. The most notable of these are the changes in the federal marginal tax schedule introduce by President George W. Bush that took effect between 2000 and 2004. There are other changes to the federal income tax system that have occurred since then such as the 2010 change to the taxation of dividend income, annual changes to the tax band thresholds and standard deductions. The main changes to tax rates occurred in the Jobs and Growth Tax Relief Reconciliation Act of 2003 and the Economic Growth and Tax Relief Reconciliation Act of 2001.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 more than 5,000 changes to the tax code between 2001 and 2012 (Erb, 2013).

In addition to the exogenous variation in the federal tax rates, we also use variation in state income tax rates as is done in Bakija and Heim (2011). Forty-three states impose some form of income tax and rates range from 0 percent on tax free allowances up to 11 percent on income over $200,000 in Hawaii. As state income tax rates are set by state legislatures, the time path of those rates varies from state to state providing temporal as well as cross-sectional exogenous variation in the state marginal income tax rates.

4 Results

We present our primary results in Table 3. We estimate equation 2.1 including (all logged) net taxable income, transfer income, net wealth+1\geq 0$, net wealth$< 0$ and other deductible expenditures (sum of mortgage interest, state taxes paid, medical expenditure and property tax paid) as well as a dummy for male household heads, marital status, years of education and the number of dependent children in the household. We also control for state and year fixed effects. We exclude endogenous itemisers though check the robustness of our results to their inclusion.

Note that conventionally, a variable distributed with a mass point at 0 with non-zero probability would be treated as censored and thus require sophisticated econometric techniques to analyse in a regression (e.g. Tobits). However, such a mass point does not necessarily indicate censoring. It is not that we do not observe donations but in fact the donation of zero is part of the choice set of the agent, (e.g Angist and Pischke, 2009). We use OLS to estimate the effect of changes in the price on the unconditional donations distribution. Similar results are found using the Correlated Random Effects Tobit (following Mundlak (1978)) are provided as a robustness check in the Appendix.

Table 3: Main results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Traditional FD	Itemiser FD	Traditional FD	Itemiser FD	Traditional FD	Itemiser FD	Traditional WG	Itemiser WG
Log price	-1.311***	-0.114	-0.072	-0.044	-0.073	-0.045	-1.420***	-0.244
	(0.159)	(0.280)	(0.326)	(0.327)	(0.326)	(0.326)	(0.159)	(0.281)
Itemiser (I)		0.436***		0.406***		0.407***		0.434***
		(0.090)		(0.140)		(0.140)		(0.091)
Start item*log price			-1.539***	-0.238				
			(0.416)	(0.610)				
Stop item*log price			-1.409***	-0.119				
			(0.419)	(0.616)				
Switcher*log price					-1.476***	-0.179		
					(0.371)	(0.583)		
Log net income	0.123*	0.188***	0.173**	0.190***	0.173**	0.190***	0.216***	0.288***
	(0.066)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.062)	(0.064)
Observations	19342	19342	19342	19342	19342	19342	26282	26282
R^2	0.019	0.020	0.020	0.020	0.020	0.020	0.041	0.043
$H_0 : \beta_{Logprice}$=-1	0.045	0.0015	0.004	0.003	0.004	0.003	0.008	0.007
$H_0 : \beta_{Start*Logprice}$=-1			0.1954	0.212				
$H_0 : \beta_{Stop*Logprice}$=-1			0.328	0.152				
$H_0 : \beta_{Switcher*Logprice}$=-1			0.328	0.152	0.199	0.159		

Notes: Results in columns (1), (3) and (5) are obtained from OLS estimation of equation 2.2 and columns (2), (4) and (6) are from OLS estimation of equation 2.9. Results for the traditonal and itemisers specificaitons in columns (7) and (8), respectively, are obtained using mean differenced data rather than first differenced data. All standard errors are obtained via a clustered (at the household level).

The estimated price elasticity from the traditional specification in column (1) is very much in line with those found in the literature. Peloza and Steel (2005) report an average price elasticity from studies using using survey data of -1.29. To address the bias in OLS-FD in model (2.1) discussed in Section 2, we estimate the 'itemiser' specification from equation 2.8 and present results in columns (2). Theorem 2 indicates that we can estimate the size of the bias by the difference the coefficient obtained from the traditional specification with that obtained from the Itemiser specification if $\bar{\tau}_1 - \bar{\tau}_{-1} = 0$. This is a testable restriction and, in fact, the estimated difference -0.0003 (p-value=0.908). As such that the estimated price elasticity obtained from the Itemiser specification is a consistent estimator of β. Comparing the results from the two specifications in Table 3 suggests the size of the bias is in excess of -1. This means that estimates of a unitary price elasticity of giving would be obtained when using survey data even if the true effect is actually 0. With the bias expunged, the point estimate of the price elasticity in column (2) is very close to 0 and is statistically insignificant at almost any significance level. This result is consistent with the bias derived in Section 2 which suggests that the estimated price effects obtained from the traditional specification are largely the result of endogenous price variation including Switchers.

We repeat this analysis in more general specifications allowing non-linearities in the response to the main variables. Column (3) considers the traditional spec. allowing the price response to differ for stop and start itemisers. We find strong evidence the responses are symmetric around -1.67 where the response to continuous itemisers is 0.07 and not statistically significant. This is to be expected as we know the price from changes in itemisation status are endogenous. Column (4) repeats (3) for the itemiser model which asymptotically removes this bias and we find little evidence switchers respond significantly differently to continuous itemisers. Given the symmetry of the effect for start and stop itemisers, we collapse them into the single category switchers in columns (5) and (6).

In columns (7) and (8), we estimate the traditional and itemisers specifications using mean differenced data, the approach more commonly used in the literature. While we do not show the bias is removed/reduced by controlling for itemisation for mean differenced data, the pattern of the results is the same. Failure to control for itemisation status leads to a strong statistically significant estimate of the price elasticity which is removed when controlling for change in itemisation status and removing (some of the) endogenous price variation.

Under the itemiser specification, the point estimates of β are all very close to, and not statistically different from, 0. However, a key drawback of the results based on the Itemiser Specification is that the variation in price controlling for itemisation is small. This explains why the standard errors on the price effect in the itemiser model are large relative to those from the traditional specification (see columns (1) and (2)). As such the estimated elasticities in the itemisers model though asymptotically unbiased are very imprecisely estimated. In the bottom rows of Table 3 we present the p-values from t-tests of the various price elasticities relative to -1. In each of the traditional specifications we find a price elasticity (in columns (3) and (5) for stop and start itemisers and for switchers, respectively) in excess of and statistically different from -1. For the itemiser specifications we find price elasticities less than and statistically different from -1. In each case, the 99% confidence regions for β in any of the itemiser specifications do not include -1. We take this as evidence that the price response in the general population is not, in fact, elastic. However, given the large standard errors, the question of whether the elasticity is closer to -1 or 0 remains open.

4.1 Non-Linear effect of ΔP

As noted in Section 2.2, interpretation of γ as a nuisance parameter will depend on the effect of changes in price being linear in the magnitude of the change. Otherwise, γ will pick up some genuine response to large changes in the price. We consider this possibility by allowing the effect of ΔP to vary with the size of ΔP and re-estimating the itemiser model. Results are presented in Table 4.

Table 4: Non-linear effect of ΔP

	(1)	(2)	(3)	(4)	(5)
	Traditional	Itemiser	Itemiser	Itemiser	Itemiser
Log price	-1.324***	-0.018	0.070	-0.052	-0.075
	(0.158)	(0.276)	(0.569)	(0.355)	(0.312)
Itemiser (I)		0.474***	0.469***	0.472***	0.468***
		(0.088)	(0.091)	(0.088)	(0.088)
Log price^2	0.116	0.122			
	(0.522)	(0.521)			
Log price*1(ΔP>0.15)			-0.105		
			(0.603)		
Log price*1(ΔP>0.25)				0.039	
				(0.320)	
Log price*1(ΔP>0.36)					0.091
					(0.321)
Log net income	0.261***	0.303***	0.305***	0.302***	0.301***
	(0.059)	(0.060)	(0.060)	(0.060)	(0.060)
Observations	19387	19387	19387	19387	19387
R^2	0.017	0.019	0.019	0.019	0.019

Notes: All results are obtained using first differneced data. All standard errors are obtained via a clustered (at the household level).

In column (1) we re-estimate the traditional model but include the square of ΔP as an additional regressor. The coefficient on the quadratic term is very close to 0 and statistically insignificant at conventional levels. We do the same for the itemiser specification in column (2) with a similar outcome. We then interact ΔP with dummies taking a value of 1 if ΔP is in the top quartile of the ΔP distribution (column (3)), in the top decile (column (4)) or in the top ventile (column (5)). In each case the coefficient on the interaction terms is close to 0 and statistically insignificant at conventional levels. We do not find evidence of a non-linear effect of ΔP.

If there were strong ommited non-linearities we would expect to find a smaller coefficient on γ suggesting we had wrongly attributed some of the price effect to the pure intercept shift between swithcers and non-switchers as discussed in Section (4). Note that in none of the itemiser specifications does the coefficient on *Itemsier*, change significantly. We take this as evidence that γ reflect the bias from switching itemisation status and not a genuine response to large changes in price that accompany changes in itemisation status.[17]

We next analyse variation in the tax-price elasticity of donations over the income distribution. Some researchers (Feldstein and taylor, 1976; Reece and Zieshang, 1985) have found that the elasticity is largest for those with lowest incomes and this elasticity decreases in income. 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. This result is at odds with economic intuition and as we show below is likely due to the bias discussed above.

Price effects by income class

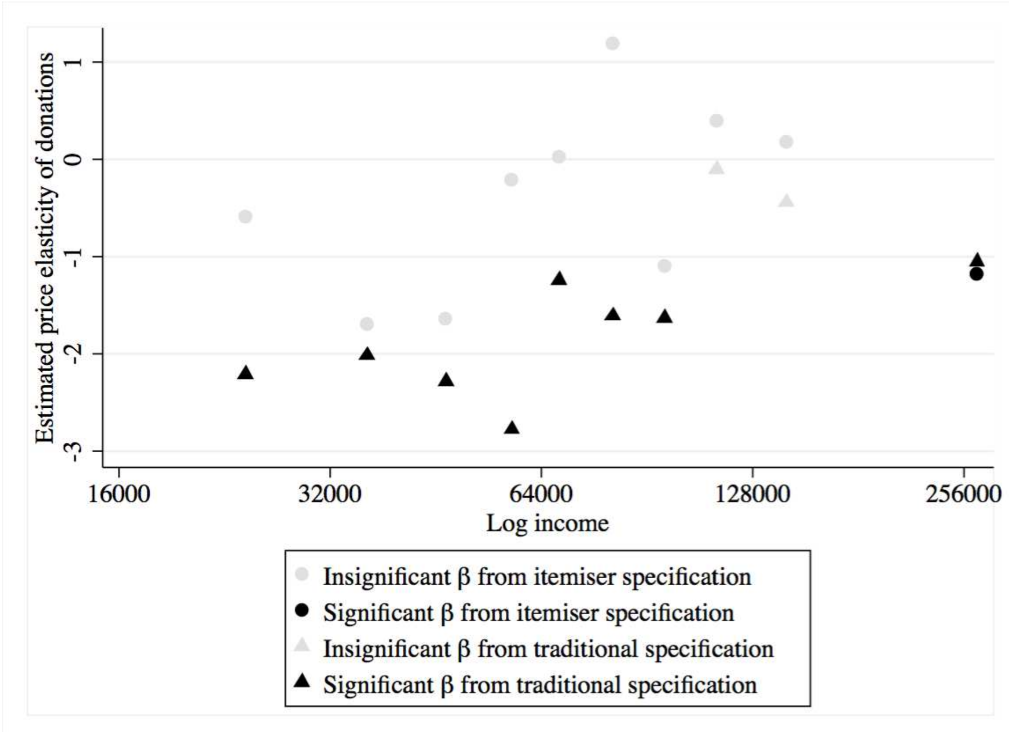
Studies using tax-filer data that omit endogenous itemisers do not suffer from the bias in Theorem 1 as agents itemise every time period and there is no bound on change in donations which leads to the bias discussed in Section 2. An example of this kind of study is Bakija and Heim (2011) who find evidence of a price elasticity in excess of -1. In our own data we obtain an estimated price elasticity of -1.10 (p-value= 0.000) when we estimate our model for exogenous itemisers only.

However, as can be seen in our own data itemisers differ from non-itemisers in their average level of income. Households in Bakija and Heim's sample have average income of over \$1 million, making them substantially wealthier from the average American household. We therefore estimate the model for different income classes to consider whether we obtain an estimate in line with papers like Bakija and Heim (2011), i.e. that higher income households respond more to changes in the price.

To do so we estimate both models for each income decile. 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}). We then plot the estimated price elasticities against the mean income of each income decile in Figure 1.

[17] This result was found considering an array of alrternative and more general non-linear price specifications that are not presented here for brevity.

Figure 1: Variation in estimated price elasticities over income



Black markers indicate a statistically significant (at the 10 percent level) estimate of β and grey markers are insignificant estimates. With the traditional specification, we find the large and significant price elasticities for lower seven income deciles and for the top decile, though the elasticity is smallest for the top decile. In each case we find that the point estimate of β obtained from the itemiser specification lies above the point estimate from the traditional specification, save for the top decile where the two point estimates are almost equivalent. Only for the top income decile is the price elasticity from the itemiser specification significant (p-value=0.079).

This overall pattern corresponds with the intuition of the bias in Theorem 1 as when income increases the probability of switching decreases (as wealthier people more likely to always itemise) which removes in part the bias from endogeneity of price for switchers. The finding in the traditional specification of a stronger price response for low to mid income individuals could in part be explained by this.

We fail to reject the required restriction for the consistency of the itemiser specification, i.e. $\bar{\tau}_1 = \bar{\tau}_{-1}$ for every decile except the first ($p-$value=0.045). As such by Theorem 1 and 2 the difference between the income elasticities in each group is a consistent estimate of the bias in the price elasticity in the standard economic model.

This provides evidence that the unusual finding in 1 that the price elasticity in the Traditional Specification is largest for those with the lowest income is due to bias. There is no obvious economic rationale for this finding and provides further support that the estimate of the price elasticity in the itemiser specification which corresponds with that found on tax filer data for those with higher incomes is a better reflection of the true price effect than the traditional specification.

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 confers a number of advantages over the use of tax filer data. In this paper we show that estimates of the price elasticity of giving obtained in the presence of non-itemisers can produce severely biased estimates.

We derived this bias formally and show that we can estimate its magnitude under a testable restriction given that we derive a simple to implement alternative specification which mitigates the bias. Empirically we find that the unbiased estimates of of the price effect are very close to and not statistically different from, 0. The bias in the estimates obtained from the Traditional specification is large, approximate of the order -1. The result is robust to the use of different sub-samples, a different data transformation and the use of a different estimator. Our results suggest that Clotfelter was right in suggesting that the average tax payer is unlikely to be responsive to the price of giving.

However, we also find evidence that higher income households are indeed responsive. Our unbiased estimates of the price effect indicate that households with incomes in excess of about $250,000 do exhibit sensitivity to changes in the price of giving with that sensitivity increasing (in absolute value) with income beyond that level. These results suggest that a rethinking of the tax deductibility of donations may be called for. From Lowry (2014) we can see that taxpayers claimed $134.5 billion in 2010, 53 percent of which is from taxpayers with income below $250,000. Our results suggest the cost of tens of billions of dollars in lost tax revenue is not resulting in any benefit in the form of increased charitable donations for the bottom 98 percent of the income distributions. 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.

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Appendix A

Proof of Theorem 1

Under the i.i.d assumption then by the Khinchine Weak Law of Large Numbers (KWLLN)

$$\hat{\beta}_{FD} \xrightarrow{p} \beta + \frac{E[u_{it}\Delta\log(P_{it})]}{E[\Delta\log(P_{it})^2]} \tag{5.1}$$

where we now show that $= E[u_{it}\Delta\log(P_{it})] < 0$ when p_1 and or p_{-1} are greater than zero where we define $p_1 = \mathcal{P}\{\Delta I_{it} = 1\}$, $p_{-1} = \mathcal{P}\{\Delta I_{it} = -1\}$, $p_0 = \mathcal{P}\{\Delta I_{it} = 0\}$. 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 itemisers defined in Section 2.

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

$$E[u_{it}\Delta \log(P_{it})|\Delta I_{it} = 0] = E[u_{it}|I_{it} = I_{i,t-1} = 1]E[\Delta \log(1-\tau_{it})|I_{it} = I_{i,t-1} = 1]p_{0,1} \quad (5.2)$$

where $p_{0,1} = \mathcal{P}\{I_{it} = I_{i,t-1} = 1\}$ and

$$E[u_{it}|I_{it} = I_{i,t-1} = 1] = E[u_{it}|E_{it} > S^*_{it}, E_{i,t-1} > S^*_{i,t-1}] = 0 \quad (5.3)$$

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

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

$$E[u_{it}\Delta \log(P_{it})] = E[\log(1-\tau_{it})u_{it}|\Delta I_{it} = 1]p_1 - E[\log(1-\tau_{i,t-1})u_{it}|\Delta I_{it} = -1]p_{-1}. \quad (5.4)$$

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

$$\Delta \log D_{it} \geq \log(D_{it}) - \log(S_{i,t-1} - E_{i,t-1}) \quad (5.5)$$

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

$$\begin{aligned} u_{it} &\geq \log(D_{it}) - \log(S_{i,t-1} - E_{i,t-1}) - \beta \log(1-\tau_{it}) && (5.6) \\ &\geq -\log(S_{i,t-1} - E_{i,t-1}) - \beta \log(1-\tau_{it}) && (5.7) \end{aligned}$$

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

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

where the second inequality follows by (5.6) and noting E_{it} is mean independent of u_{it} since we can control for (polynomials of) E_{it}.[18] The final inequality follows as $E[u_{it}] = 0$ (by assumption

[18] 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.

or via inclusion of a constant) then defining $p_{11} = \mathcal{P}\{u_{it} \geq h_{it}\}$

$$0 = E[u_{it}] = E[u_{it}|u_{it} \geq h_{it}]p_{11} + E[u_{it}|u_{it} \leq h_{it}](1 - p_{11}) \tag{5.8}$$

where $-\beta \log(1-\tau_{it}) \leq 0$ and $-\log(S_{i,t-1} - E_{i,t-1}) \leq 0$ (which binds for some i,t)so that $E[u_{it}|u_{it} \leq h_{it}] < 0$ which implies by (5.8) that

$$E\left[u_{it}|u_{it} \geq h_{it}\right] > 0. \tag{5.9}$$

By independence of τ_{is} and u_{it}

$$E[\log(1-\tau_{it})u_{it}|\Delta I_{it} = 1] = E[\log(1-\tau_{it})|\Delta I_{it} = 1]E[u_{it}|\Delta I_{it} = 1] \tag{5.10}$$

and since $\log(1-\tau_{it}) \leq 0$. for all i,t and is strictly less than zero for some i,t then $E[\log(1-\tau_{it})|\Delta I_{it} = 1] < 0$ so that

$$E[\log(1-\tau_{it})u_{it}|\Delta I_{it} = 1] \leq E[\log(1-\tau_{it})|\Delta I_{it} = 1]E[u_{it}|u_{it} \geq h_{it}] \tag{5.11}$$

Together (5.9), (5.11) imply

$$E[\log(1-\tau_{it})u_{it}|\Delta I_{it} = 1] < 0 \tag{5.12}$$

We now consider the second term in the RHS of (5.4) for $\Delta I_{it} = -1$. By a similar argument to the case $\Delta I_{it} = 1$

$$u_{it} \leq \log(S_{it} - E_{it}) - \beta \log(1-\tau_{i,t-1}) - \log(D_{i,t-1}) \tag{5.13}$$

$$\leq \log(S_{it} - E_{it}) \tag{5.14}$$

as $-\log(D_{i,t-1}) \leq 0$ and $-\beta \log(1-\tau_{i,t-1}) \leq 0$ as $\beta \leq 0$

$$-E[\log(1-\tau_{i,t-1})u_{it}|\Delta I_{it} = -1] = E[-\log(1-\tau_{i,t-1})|\Delta I_{it} = -1]E[u_{it}|\Delta I_{it} = -1] \tag{5.15}$$

$$E[u_{it}|\Delta I_{it} = -1] \leq E[u_{it}|u_{it} \leq \log(S_{it} - E_{it})] \tag{5.16}$$

$$< 0 \tag{5.17}$$

by a similar argument to above 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

$$-E[\log(1 - \tau_{i,t-1})u_{it}|\Delta I_{it} = -1] < 0. \tag{5.18}$$

Then together (5.12) and (5.18) plugged in to (5.4) imply

$$E[\Delta \log(P_{it})u_{it}] < 0 \tag{5.19}$$

if either p_1, p_{-1} is strictly greater then zero.

Proof of Theorem 2

We specify our itemiser specification (Equation (2.2) in the text)

$$\Delta \log(D_{it}) = \gamma \Delta I_{it} + \beta \Delta \log(P_{it}) + \omega' \Delta X_{it} + e_{it} \tag{5.20}$$

where $u_{it} = e_{it} + \gamma \Delta I_{it}$ and $\gamma > 0$ as seen in the proof of Theorem 1 above as $E[u_{it}|\Delta I_{it} = -1] < 0$, $E[u_{it}|\Delta I_{it} = 1] > 0$ and $E[u_{it}|\Delta I_{it} = 0] = 0$.

Under the i.i.d assumption by an application of KWLLN

$$\hat{\theta}^I_{FD} \overset{p}{\to} E[w_{it}w'_{it}]^{-1}E[w_{it}\Delta \log(D_{it})] \tag{5.21}$$

$$= \begin{pmatrix} \gamma \\ \beta \\ \omega \end{pmatrix} + \begin{pmatrix} E[z_{it}z'_{it}] & E[z_{it}\Delta X'_{it}] \\ E[\Delta X'_{it}z_{it}] & E[\Delta X_{it}\Delta X'_{it}] \end{pmatrix}^{-1} \begin{pmatrix} E[e_{it}z_{it}] \\ E[e_{it}\Delta X_{it}] \end{pmatrix} \tag{5.22}$$

where the second equation follows plugging in $\Delta \log(D_{it}) = \gamma \Delta I_{it} + \beta \Delta \log(P_{it}) + \omega' \Delta X_{it} + e_{it}$ and expanding out. Then as $E[e_{it}\Delta X_{it}] = 0$ (and/or $E[z_{it}\Delta X'_{it}]$=0) then it follows by (5.22) (noting $z_{it} = (\Delta I_{it}, \Delta \log(P_{it})')$

$$
\begin{aligned}
\begin{pmatrix} \hat{\gamma}^I_{FD} \\ \hat{\beta}^I_{FD} \end{pmatrix} &\overset{p}{\to} \begin{pmatrix} \gamma \\ \beta \end{pmatrix} + E[z_{it}z_{it}']^{-1}E[e_{it}z_{it}] \\
&= \begin{pmatrix} \gamma \\ \beta \end{pmatrix} + \begin{pmatrix} E[(\Delta I_{it})^2] & E[\Delta I_{it}\Delta \log(P_{it}] \\ E[\Delta I_{it}\Delta \log(P_{it})] & E[(\Delta \log(P_{it}))^2] \end{pmatrix}^{-1} \begin{pmatrix} E[e_{it}\Delta I_{it}] \\ E[e_{it}\Delta \log(P_{it})] \end{pmatrix} \\
&= \begin{pmatrix} \gamma \\ \beta \end{pmatrix} + \frac{1}{\det(E[z_{it}z_{it}'])} \begin{pmatrix} E[(\Delta \log(P_{it}))^2] & -E[\Delta I_{it}\Delta \log(P_{it}] \\ -E[\Delta I_{it}\Delta \log(P_{it})] & E[(\Delta I_{it})^2] \end{pmatrix} \begin{pmatrix} E[e_{it}\Delta I_{it}] \\ E[e_{it}\Delta \log(P_{it})] \end{pmatrix}
\end{aligned}
$$

Expanding out the second element in the limit and defining $C = \det(E[z_{it}z_{it}'])$

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

where the second equality follows as

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

where $\bar{\tau}_1 = E[\log(1 - \tau_{it}|\Delta I_{it} = 1]$, $\bar{\tau}_{-1} = E[\log(1 - \tau_{i,t-1})|\Delta I_{it} = -1]$.

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

and the final equality uses the LIE and strict exogeneity of τ_{it}
$E[e_{it}\Delta \log(P_{it})] = E[e_{it}|\Delta I_{it} = 1]\bar{\tau}_1 p_1 - E[e_{it}|\Delta I_{it} = -1]\bar{\tau}_{-1}p_{-1}$ and

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

$$E[e_{it}\Delta\log(P_{it})] - \bar{\tau}_1 E[e_{it}\Delta I_{it}] = (\bar{\tau}_1 - \bar{\tau}_{-1})E[e_{it}|\Delta I_{it} = -1]p_{-1} \tag{5.23}$$

and by a similar argument

$$E[e_{it}\Delta\log(P_{it})] - \bar{\tau}_{-1} E[e_{it}\Delta I_{it}] = (\bar{\tau}_1 - \bar{\tau}_{-1})E[e_{it}|\Delta I_{it} = 1]p_1 \tag{5.24}$$

Appendix B

Robustness checks

We carry out a number of robustness checks. First we consider the use of an instrumental variable approach when we use P^{First} and an instrument for P^{Last}. We do this with both the first differenced and the mean different data for both the traditional and itemiser specifications.

Table B.1: Robustness check I: Instrumental variables

	(1)	(2)	(3)	(4)
	FD IV Traditional	FD IV Itemiser	WG IV Traditional	WG IV Itememiser
Log price	-1.411***	-0.130	-1.574***	-0.331
	(0.168)	(0.331)	(0.160)	(0.310)
Itemiser (I)		0.439***		0.436***
		(0.099)		(0.095)
Log net income	0.120*	0.184***	0.228***	0.301***
	(0.064)	(0.067)	(0.058)	(0.061)
Observations	19936	19936	27003	27003
R^2	0.015	0.017	0.039	0.040
idp	0.000	0.000	0.000	0.000
First Stage tests				
A-P weak inst.	0.000	0.000	0.000	0.000
Shea's partial R^2		0.904		0.675

Notes: Results obtained from OLS estimation of equation X with mena differnced data. All standard errors are obtained via a clustered (at the household level) bootstrap with 500 replications.

The p-value from a t-test of our restriction $\bar{\tau}_1 = \bar{\tau}_{-1}$ is 0.2682. Again we estimate a bias of an order around -1.1 and find results consistent with the OLS results in Table 3.

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 (Chamberlain, 1982) 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 5.

Table B.2: Robustness checks II: CRE Tobits

	(1)	(2)
	Traditional	Itemiser
Log price	-1.128***	-0.012
	(0.134)	(0.223)
Itemiser (I)		0.424***
		(0.076)
Log net income	0.169***	0.248***
	(0.055)	(0.058)
Observations	27018	27018
Pseudo R2	0.081	0.084
LL	-58380.357	-58141.325

Notes:

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