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Correlated Random Effects Quantile Estimation of the Tax-Price Elasticity of Charitable Donations

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Abstract

This paper provides quantile estimates of the tax-price elasticity of charitable donations controlling for unobserved heterogeneity. Utilising the Correlated Random Effects Quantile estimator of Bache, Dahl & Kristensen (2013) it is found that the size of the price elasticity is decreasing in the size of donation with very large donors being largely unresponsive to tax incentives for giving. We provide evidence that cross sectional quantiles estimates of the price elasticity not accounting for unobserved heterogeneity suffer a substantial downward bias for those with small to mid-level donations.

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1 Introduction

A large literature has developed aiming to estimate the price elasticity of charitable giving. Much of the existing literature has focussed on estimating the price elasticity around the mean, though the distribution of donations in the US and other countries is bimodal, with a large mass of zero and large donations. This is important as the responsiveness of donations to price around the mean may not be reflective of how larger donors respond, who comprise a large portion of total donations to charitable causes.

Only a small number of studies have begun to consider heterogeneity in the price effect over the conditional donation distribution, though results are mixed. Fack and Landais (2010) use data from France and a discontinuity in the French incentive for giving to find evidence that the tax incentive for giving there may affect large donations but not small ones. Lin and Lo (2012) use a cross section of US taxpayers and find price elasticities around -5 for small donations which decrease in absolute size with the responsiveness of larger donations to price being close to zero. Bönke et al. (2013) estimate the impact of the tax incentive for giving in Germany using a large pooled cross-section of German taxpayers. Their results suggest the price effect is largest (in absolute value) for small and large donations with donations in the middle of the distribution relatively less affected by changes in the price of giving.

A potential problem with these initial results estimating price elasticities across the quantiles of donations is they do not address the issue of unobserved heterogeneity. This problem is well accounted for in the research estimating price elasticities around the conditional mean of donations. Peloza & Steel (2005) provide a detailed meta-analysis of the results in the literature and find on average panel data estimates of the price elasticity are significantly smaller (in absolute value) than those based on cross sectional data.

The main contribution of this paper is to use the Correlated Random Effects (CRE) Quantile estimator set out in Bache, Dahl & Kristensen (2013) [BDK] to estimate the price elasticity of charitable giving in the US across the quantiles of the donations distribution. We find evidence utilising this approach that the price elasticities for small to mid-range donors are substantially smaller in absolute size than those utilising standard pooled quantile estimates.

2 Quantile Estimation of Tax-Price Elasticity of Giving

In the US personal charitable donations (D^*_{it}) are tax deductible. Namely when total donations and other tax deductible expenditures (E_{it}) are greater than the standard tax deduction (S^*_{it}) an agent can deduct total expenditures, yielding a price of donating one dollar $P_{it} = 1 - I_{it}\tau_{it}$ where $I_{it} = 1(D^*_{it} + E_{it} > S^*_{it})$ (Itemisation Dummy) and τ_{it} is the marginal rate of taxation. The traditional economic model for the price elasticity around the mean in the literature is

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

where $D_{it} = D^*_{it} + 1$ and W_{it} is a vector of personal characteristics including income and wealth and α_i is all time invariant unobserved heterogeneity.[1] A now sizeable literature has emerged estimating β using panel data where Within Group type estimators remove likely endogeneity from omitted unobserved heterogeneity. For example higher donors more likely to itemise and hence face a lower price, yielding a downward bias in the estimator of the price elasticity as noted in Backus & Grant (2016).

These omitted variables likely cause a substantial downward bias in the price elasticity of giving as is well known in the literature and verified in the meta-analysis of Peloza & Steel (2005). This unobserved heterogeneity will also be apparent when estimating the price elasticity across the quantiles of the distribution of donation. As such we consider the quantile equivalent of the linear model utilising the CRE model of BDK.

Define $X_{it} = (\log(P_{it}), W_{it})$, $Z_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}$, where we assume X_{it} is i.i.d. The 'CRE' model in BDK allows Fixed Effects (FE) in a similar way to the CRE of Chamberlain (1984) modelling the conditional mean, but assuming that the FE at any quantile (τ) is a projection on to the time averages of the regressors Z_i.[2] The 'A.CRE' assumption (omitting subscripts for brevity)

$$\log(D) = Q(X, Z, U) \qquad U|X, Z \sim \text{Unif}(0, 1) \tag{2.2}$$

$$Q(X, Z, \tau) = \beta(\tau)\log(P) + \theta(\tau)' W + \pi(\tau)' Z \tag{2.3}$$

[1] We take a positive transformation of the level of donation such that the log exists as is standard in the donations literature.

[2] As noted in BDK the CRE model is a special case of that in Abrevaya & Dahl (2008) which is applicable in unbalanced panels as in this paper. See page 1602 of BDK for more details.

where $Q(X, Z, \tau)$ is the τ quantile of $\log(D)$ given X, Z.[34] Under the A.CRE assumption then $\beta(\tau)$ (and the corresponding coefficients on the controls $\theta(\tau)$) can be estimated by the quantile estimator in Koenker & Bassett (1978).[5]

The assumption in (2.3) is the quantile generalisation of the CRE estimator of Chamberlain (1984). Intuitively for this problem it assumes this time invariant unobserved heterogeneity is linear in the average price, age, wealth etc. of an individual. We argue this assumption is not too unrealistic in this setting given the comprehensive nature of the control set considered in this paper. Though there may still exist some further endogenous variation in this time invariant unobserved heterogeneity violating (2.3), it is likely this estimator is likely to substantially reduce the bias relative to the standard pooled quantile estimator.

3 Data

We use data from the Panel Study of Income Dynamics (PSID), a bi-annual survey of US households. The focus of the PSID is economic and demographic, with comprehensive detail on income sources and amounts, certain types of expenditure, education, household composition and residential location. In 2000, the PSID introduced the Center on Philanthropy Panel Study (COPPS) module containing questions on giving and volunteering.

We use seven waves of the PSID covering 2000-2012 giving us a raw sample with 58,993 observations. Following Backus & Grant (2016) we 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 27,063 observations (5,845 households appearing for an average of 5.4 years).[6] Marginal tax rates are computed using the National Bureau of Economic Research's Taxsim programme (Feenberg and Couts, 1993). . We calculate the price based on the first dollar of giving

[3] See pages page 1601 of BDK.

[4] As is standard in the literature on giving we use the marginal rate of tax on the first dollar of giving to form the price P_{it} which is arguably exogenous once we control for income and other factors. Also the correlation between the tax on the first and last dollar is 0.97 so the possible bias from any endogenoeity is small.

[5] See page 1610 of BDK for more details.

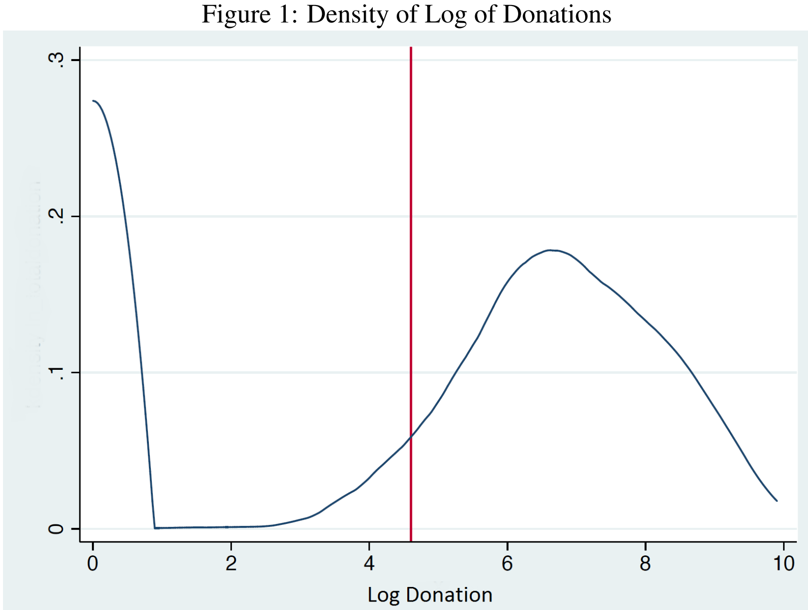
[6] As standard in the donation literature we remove from the sample 'Endogenous Itemisers', i.e those who conditional on their other tax deductible expenditures, itemise their tax returns because of their level of donation. The price of donating for these individuals is implicitly a function of donation and hence endogenous. Endogenous Itemisers represent only 2% of the PSID sample.

$$\tau_{it} = \left[\tau^F_{it} + \delta^S_{it}\tau^S_{it} - \tau^S_{it}\tau^F_{it}\delta^F_{it}\right] \tag{3.1}$$

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.

Figure 1 plots the density of $\log(D_{it})$ where the red horizontal line is the sample mean. As can be seen the distribution of $\log(D_{it})$ is bifurcated with a large mass of zero and large donations. This part motivates studying the price elasticity not just around the mean, but across the quantiles of the distribution, especially the high and low level donors.[7]

Figure 1: Density of Log of Donations



4 Empirical Results

This section presents the estimates of the price elasticity across the quantiles of the distribution of donations. Figure 2 presents the estimates from the linear quantile estimator of Koenker & Bassett (1978) pooling the observations. The absolute size of price elasticity is decreasing (in absolute value) in the level of donation, being around -4 to -5 for those with small donations and inelastic and close to zero for larger donations. The

[7] The distribution of donations looks unusual at low donations as there is a mass of non-zero donors and no donations at lower level donations up to around exp(2.5) which is around $13.

estimated elasticities over the quantile of donations in Figure 2 looks very similar to those found in Lin & Lo (2012) using US data. As in Lin & Lo (2012) the estimated elasticities for smaller donations are very large. A likely reason for this finding as noted in Section 2 is the pooled estimator does not account for endogenous unobserved heterogeneity.

Figure 2: Pooled Quantile Elasticity Estimates

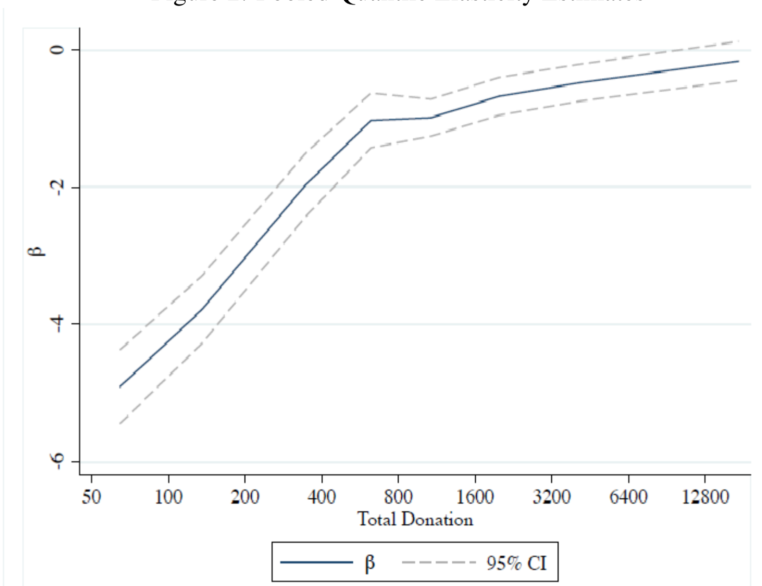


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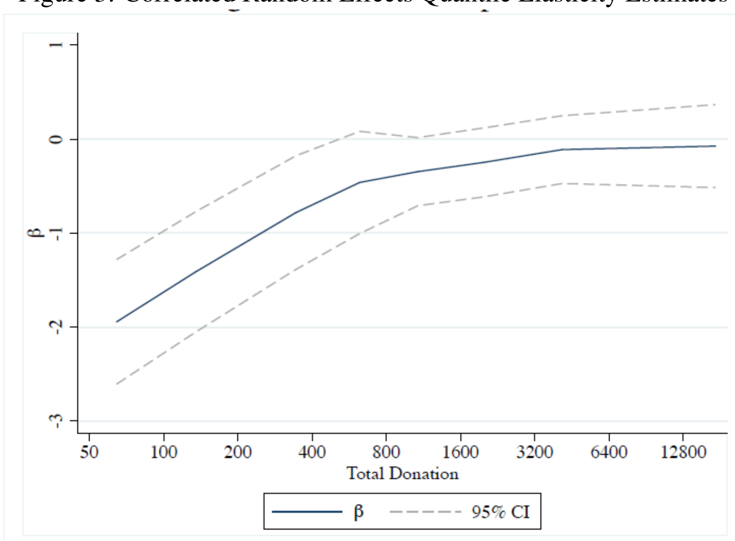
Figure 3: Correlated Random Effects Quantile Elasticity Estimates



To reduce this bias we consider the CRE estimator detailed in Section 2 with estimates provided in Figure 3. The estimated coefficients of the control variables across various quantiles in are presented in Table 1 in the Appendix where the estimated coefficients confirm with economic intuition across various quantiles.

The Pooled Quantile estimates finds very large elasticities at lower donations, decreasing in the size of donation with evidence they are statistically indistinguishable from zero at the 5% significance level for all levels of donations above $6400. The CRE Quantile Estimates also decrease in absolute size in the level of donation, though are smaller in absolute value relative to the pooled estimator across the quantiles, especially so at lower level donations. Finally we cannot reject the null that the responsiveness of donations to price is found to be zero at the 5% level for all donations above $400.

One explanation for this is that the CRE models has accounted for at least some of the endogenous unobserved heterogeneity, removing or reducing the negative bias in the pooled quantile estimator.The results suggest that the responsiveness to tax incentives (i.e the price) is strongest for those with smaller donations, though not as large as we would find using cross sectional data as in Lin & Lo (2012) and others.

Lin & Lo (2012) also find larger donors are unresponsive to price. It may be that larger donations are more likely to be bequests and not responsive to year to year changes in the marginal tax schedule where smaller donations are more likely be made yearly and may respond to changes in tax (and hence price).

5 Conclusion

We provide quantile estimates of the price elasticity of giving in the US that addresses the issue of endogenous unobserved heterogeneity. Using the Correlated Random Effects Quantile Estimator of Bache, Dahl & Kristensen (2013) we find a price elasticity decreasing in absolute size in the level of donation, being close to zero for very large donations. We provide evidence that price elasticities for smaller donations using the pooled quantile estimator suffer a substantial negative bias. Accounting for unobserved heterogeneity we find elasticities around one third the size than those estimated on pooled data for smaller donors.

6 Appendix

Table 1 below reports the estimates of the coefficients of the controls $\theta(\tau)$ from (2.3) for the 40,50,60,70,80,90 and 99th percentile. The effects of $\log(age)$ is found to be positive and large with high probability across the quantiles and likewise for $\log(income)$ as we would expect. Correspondingly there is little evidence of any effect of having high school or college degrees across the quantiles, possibly in part due to the small variation in these variables over time. It is not obvious a priori how being married or having children would impact donations. Possibly there would be some positive impact as married people and/or with children are more likely to be integrated in the community and be more likely to donate. It is found the effect of being married and children decreases for higher donors with strong evidence of a positive effect aside from in the 99th percentile. There is some evidence other tax deductible expenditures have a positive effect at low to mid level quantiles of donations, which may in part reflect an income effect as those with higher expenses have more income.

Table 1: Estimated Coefficients on Controls

	q40	q50	q60	q70	q80	q90	q99
Log age	2.592***	3.720***	3.364***	2.185***	1.920***	2.143***	1.219***
	(0.566)	(0.535)	(0.481)	(0.320)	(0.324)	(0.319)	(0.390)
Married^d	0.917***	0.797***	0.459***	0.258***	0.231**	0.186**	-0.020
	(0.157)	(0.148)	(0.133)	(0.089)	(0.090)	(0.088)	(0.108)
Non-HS grad^d	0.169	0.325	0.094	0.039	0.071	0.045	-0.059
	(0.326)	(0.308)	(0.277)	(0.184)	(0.187)	(0.183)	(0.225)
Some college^d	0.212	0.030	0.039	0.066	0.117	0.060	-0.071
	(0.223)	(0.211)	(0.189)	(0.126)	(0.128)	(0.126)	(0.154)
College^d	0.099	0.154	0.116	0.078	-0.026	-0.048	0.061
	(0.310)	(0.292)	(0.263)	(0.175)	(0.177)	(0.174)	(0.213)
Grad school^d	0.226	0.166	0.134	0.111	0.043	0.158	0.121
	(0.355)	(0.335)	(0.301)	(0.201)	(0.203)	(0.200)	(0.244)
Children^d	0.197***	0.150***	0.103**	0.114***	0.098***	0.122***	0.005
	(0.053)	(0.050)	(0.045)	(0.030)	(0.031)	(0.030)	(0.037)
Log income	0.389***	0.461***	0.460***	0.421***	0.306***	0.260***	0.473***
	(0.105)	(0.099)	(0.089)	(0.060)	(0.060)	(0.059)	(0.073)
Log expenses	0.539**	0.652***	0.442**	0.089	0.083	0.205	0.140
	(0.264)	(0.249)	(0.224)	(0.149)	(0.151)	(0.149)	(0.182)
Observations	27063	27063	27063	27063	27063	27063	27063

Notes: Variables with ^{d} are dummies. *** refers to a test that the corresponding parameter is zero at the 1%. Similarly ** denotes a 5% significance level and * a 1% significance level.)

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