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REVISITING THE PRICE ELASTICITY OF CHARITABLE GIVING: META-ANALYSIS OF TAX INCENTIVES AND MATCHING DONATIONS

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Abstract

This paper presents the first quantitative meta-analysis of the price elasticity of charitable giving under both rebate and matching schemes. We compile 151 elasticity estimates from 33 experimental studies and synthesize them using random-effects and multi-level models. Charitable giving is highly price-responsive: the pooled meta-analytic mean elasticity of total donations is −1.25, indicating that lowering the effective price of giving substantially increases charitable revenue. Although we observe considerable between-study heterogeneity and some evidence of publication bias, bias-adjusted estimates remain negative. Furthermore, elasticity is substantially more negative under matching (−1.98) than under rebate (−0.87), contradicting the theoretical prediction of equivalence but aligning with the original experimental findings in this literature. The rebate-matching difference is attenuated when moving from laboratory to field settings, although it persists.

JEL Classification codes: C90, D91, H20
Keywords: charitable giving, rebate, matching, experiment, meta-analysis

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1 Introduction

Understanding the price elasticity of charitable giving—the extent to which donors respond to changes in the price of giving—is essential for designing price-based donation policies. In practice, the effective price of giving is determined by two institutional mechanisms: tax deductions provided by governments and matching donations offered by corporations and foundations. These *rebate* and *matching* schemes are therefore the key policy tools for lowering the effective price of charitable contributions.

Standard economic theory predicts that, under controlled conditions, rebate and matching schemes should induce identical behavioral responses, as long as they reduce the price of giving by the same proportion. Specifically, a 1:1 matching subsidy is economically equivalent to a 50% rebate: under a 1:1 matching scheme, when an individual donates \$50 to a charity, an additional \$50 is contributed through matching, resulting in a total contribution of \$100 to the charity. In contrast, under a 50% rebate scheme, an individual donates \$100 and receives a \$50 refund, again incurring an effective out-of-pocket cost of \$50. In both cases, the donor generates a \$100 total contribution at an effective cost of \$50, implying that the two incentive structures are equivalent. Similarly, a 2:1 match corresponds to approximately a 33% rebate, and a 4:1 match corresponds to a 20% rebate, assuming the price of giving is held constant. The relationship between the matching rate (m) and the rebate rate (r) can be expressed as:

$$m = \frac{r}{1 - r}.$$

Building on this equivalence, previous studies commonly posit that rebate and matching schemes share the same price elasticity of charitable giving with respect to total giving—the total amount received by the charity (e.g., Eckel and Grossman, 2003). In other words, when the price of giving decreases by a certain proportion, both schemes are theoretically expected to produce an equivalent increase in total donations. The exact prediction extends to net giving—the donor's final out-of-pocket expenditure after accounting for rebates—which is likewise expected to exhibit the same price elasticity under the two schemes.

These predictions are linked to a further hypothesis that the price elasticity of checkbook giving—the initial amount selected by the donor—is larger in absolute value under the rebate scheme than under the matching scheme. Specifically, when the price of giving decreases by a given proportion, the rebate scheme is expected to increase checkbook giving, whereas the matching scheme is expected to decrease it.

The seminal study by Eckel and Grossman (2003) experimentally demonstrated that, contrary to the theoretical prediction of equivalence between rebate and matching schemes, the two produce distinct effects on charitable behavior. In their controlled laboratory experiment, where the price of giving was held constant across treatments, total giving was consistently and significantly higher under the matching condition, with differences ranging from approximately 20% to 100%, even when the effective price was equivalent. Moreover, the estimated price elasticity of donations was −0.34 under the rebate condition and −1.07 under the matching condition, indicating that matching implied roughly three times stronger responsiveness to price changes than rebate. Thus, their study was the first to provide experimental evidence that, although the two schemes should theoretically yield identical effects, they actually generate systematically different behavioral responses in practice.

To examine how general and replicable this phenomenon is, a large number of studies have subsequently tested the robustness of the findings by Eckel and Grossman (2003). In addition to their own follow-up investigations (Eckel and Grossman, 2006, 2008*a*,*b*), several research groups refined the experimental design by examining the possibility that participants might not have fully understood how the mechanisms worked and by further clarifying how the two schemes differ along the budget constraint while explicitly controlling for such differences (Davis and Millner, 2005; Davis et al., 2005; Davis, 2006; Lukas et al., 2010; Blumenthal et al., 2012). Furthermore, this line of research has extended beyond the laboratory to field experiments conducted in real donation contexts (Eckel and Grossman, 2017) and to cross-national and cross-sample replications (Sasaki et al., 2022). Overall, these studies have generally confirmed that matching schemes tend to generate higher total giving and larger price elasticities than rebate schemes. However, the magnitudes of these differences vary considerably across studies. For instance, in Eckel and Grossman (2006), the price elasticity of total giving was estimated to be −1.491 under the rebate condition and −3.174 under the matching condition, whereas in Blumenthal et al. (2012) it was −0.23 and −0.75, respectively.

Taken together, these findings highlight the need to systematically synthesize existing evidence and quantitatively compare and evaluate how rebate and matching schemes affect total giving, checkbook giving, and their price elasticities. To address this issue, the present study conducts a meta-analysis of existing experimental studies to comprehensively examine the relative patterns of price responsiveness between the two subsidy schemes.

We begin by conducting a systematic search of published and unpublished studies in economics, public policy, and related fields to identify experiments—both laboratory and field—that exogenously manipulate the marginal price of giving through matching or rebate schemes. For each study, we extract or compute a standardized elasticity measure (for checkbook, net, and total giving) and its corresponding standard error to ensure comparability across experimental settings, sample populations, and treatment types. We identify 33 primary studies and extract (or compute) 151 measures of price elasticities. Figure 1 provides an initial overview of the evidence in the literature. The unweighted distributions of elasticities reveal substantial heterogeneity as well as potential differences between donations made under matching schemes and those made under rebate schemes.

We then apply meta-analytic methods, including random-effects models and their multilevel extensions, as well as publication bias correction techniques, to estimate the pooled price elasticity of charitable giving, quantify heterogeneity across studies, assess the extent of

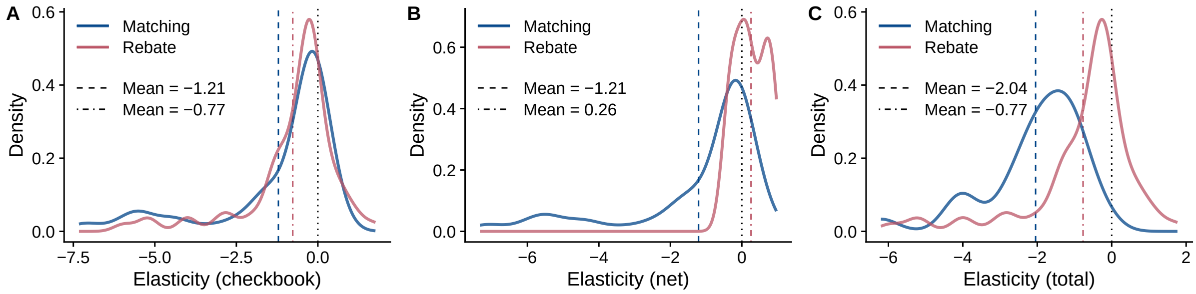

FIGURE 1: Distributions of price elasticities of charitable donations under rebate and matching schemes. (A) Checkbook donation ($N = 150$). (B) Net donation ($N = 107$). (C) Total donation ($N = 97$). *Notes*: Checkbook elasticity represents the initial amount contributed by the donor, before applying either the match or the rebate. Total elasticity refers to the money received by the charity, and the net donation is the amount effectively paid by the donor, once a rebate has been taken into account. The kernel density estimate of the distribution is displayed, computed using a Gaussian kernel and a bandwidth selected according to Silverman's rule of thumb.

publication bias, and obtain a bias-adjusted elasticity estimate (Irsova et al., 2024; Stanley and Doucouliagos, 2012). We find that the meta-analytic average price elasticity of total donations is −1.247 (95% CI [−1.879, −0.614]), indicating that reducing the donation price significantly increases donations. We find evidence of publication bias, but even after adjusting for it, the price elasticity remains negative, although its magnitude is reduced.

Turning to the comparison between matching and rebate schemes, we find that experimental participants are more responsive to price changes when using matching schemes than when using rebates. The meta-analytic average elasticity of total donations is −1.977 (95% CI [−3.100, −0.853]) under matching, but only −0.871 (95% CI [−1.582, −0.160]) under rebates. Beyond this, we do not identify other moderators that consistently account for variation in the reported elasticities. In particular, we find no evidence that laboratory studies and field experiments report significantly different results.

A few comprehensive review studies have previously synthesized evidence on donation incentives such as rebates and matching schemes. However, compared with these studies, our meta-analysis is methodologically and substantively distinct. Saeri et al. (2023) and Chapman and Thai (forthcoming) conduct broad systematic reviews of charitable giving interventions discussing the effects of rebates and matching conceptually. However, neither provided a quantitative synthesis that integrates and directly compares their effect sizes using a common metric. In contrast, Peloza and Steel (2005), Salmon (2024), and Hung et al. (2025) offer rigorous quantitative meta-analyses estimating the tax price elasticity of giving, but all three focus exclusively on rebate (tax deductibility) schemes and do not examine matching incentives. Epperson and Reif (2019) present a comprehensive review focused on matching subsidies and discusses theoretical contrasts with rebate mechanisms, but without conducting a statistical meta-analysis of effect sizes. Our study complements the existing evidence syntheses by providing the first quantitative meta-analysis that directly compares rebate and matching schemes, assessing their respective effects on price elasticities using a unified empirical framework.

The rest of the paper is structured as follows. Section 2 explains how we construct the dataset. Section 3 describes the overview of the literature. Section 4 presents the meta-analytic results.

2 Data

2.1 Identification and Selection of Relevant Studies

To obtain an unbiased meta-analysis, we initially identified and selected relevant studies, strictly adhering to our inclusion criteria. The main criterion was to include papers that report a price elasticity of giving, or from which we can compute an elasticity. Under this criterion, we included papers that use experimental methods, both laboratory and field.

We searched for relevant papers on two databases, Web of Science and Google Scholar. The initial systematic search was conducted in February 2025, yielding 860 studies from Web of Science and 996 studies from Google Scholar. Therefore, a total of 1,578 papers were identified from both databases, after removing exact duplicates (i.e., identical hits from Web of Science and Google Scholar).

We selected papers based on six criteria. First, we only considered original research papers; that is, we excluded book chapters, policy briefs, Ph.D. or Master's theses, and conference proceedings. Second, we focused on empirical papers, excluding those that were purely theoretical or simulation-based. Third, we focused on papers that emphasize charitable donations (as opposed to, for example, taxation). Fourth, because we want to use price variation as one of our main moderators of price elasticity, we only selected papers where the price variation can be computed. This criterion implies that we excluded studies employing threshold-type or non-linear matching schemes (e.g., Adena and Huck, 2022; Castillo et al., 2023), and focused solely on linear matching mechanisms. This also enables direct comparison with linear rebate schemes. Fifth, we only selected papers for which donations were an outcome, meaning papers such as Xiao and Yue (2021), which focused on donor retention, were excluded. Finally, we only included experimental papers to facilitate comparability.

After applying the selection criteria, we were left with 151 point estimates from 33 papers (35 conceptually distinct studies) for the analysis. The details of the search and selection procedure are summarized in Online Appendix A.1. The final list of papers is presented in Online Appendix C.

2.2 Data Construction

We constructed the dataset of our meta-analysis by coding the relevant information we gathered from the 33 papers—price variation, elasticities of giving and their associated standard errors (SEs), characteristics of the study, and methodological information.

The two primary variables of interest are price variations and elasticities. For the price variation variables, we created the variable d_p as follows. For rebates, it is defined directly as the negative of the rebate share. For matching, it is defined as the negative share of the total donation that is given by the matching grant. The price variation for a 2:1 matching treatment is therefore the same as that of a 33% rebate, and is -0.33.

Second, we recorded—or computed—the price elasticities of charitable donations. If the elasticity is estimated in the paper, we included it as is. If, however, the authors did not report the elasticity, we imputed the elasticity using equation (1) below, based on the treatment effects, means, and standard deviations (SDs) of the treatment and control groups:

$$e = \frac{\Delta\text{Donation}}{\text{Donation}}\frac{1}{d_p}. \tag{1}$$

Details are provided in Appendix A.2. We recorded (or computed) corresponding standard errors (SEs) of parameter estimates accordingly.

We gathered three types of price elasticities of donations: checkbook donations, total donations, and net donations.[1] A checkbook donation refers to the amount paid by the donor. The total donation refers to the amount received by the charity, while the net donation represents the final amount for the individual, after deducting any potential rebates. Therefore, the checkbook and net donations are the same for matching treatments, while the checkbook and total donations are identical for rebate treatments. In the analysis, we put more weight on total donations, because theoretical predictions of equivalence are fundamentally framed in terms of total donations (e.g., Eckel and Grossman, 2003).

Next, we coded the variables that would describe the measurement methods and characteristics of the studies. These included details such as location (country and continent); type of experiment (field, laboratory, online, etc.); type of incentivization (own or windfall money); subject population (university students, general population, online pool, targeted sample); the measurement of effect (i.e., elasticity parameters, treatment effects, SEs, etc.); type of treatment (matching or rebate, level of price variation) and several others. The complete list of coded variables is available in Table A.1 in the online appendix.

3 Features of Studies

In total, 33 unique experimental papers, covering 35 conceptually different studies, were identified. As of November 2025, 32 of these papers had been published across 16 peer-reviewed

[1]The terminology used in the literature to describe donation outcomes is often highly inconsistent: many papers employ multiple terms for the same concept, and some terms are used with different meanings across studies and even within individual studies. To ensure comparability, we carefully verified that all elasticity measures included in our meta-analysis align with the definitions provided above.

Table 1: Characteristics of the studies.

	N	Share		N	Share
Type of experiment			*Location of the study*		
Laboratory	15	0.43	Americas	23	0.70
Natural field	14	0.40	Europe	6	0.18
Online	6	0.17	Asia	3	0.09
			Multiple	1	0.03
Design			*Recipient type*		
Between subject	25	0.74	Poverty	4	0.12
Within subject	8	0.24	Environment	3	0.09
Mixed	1	0.03	Education	2	0.06
			Children and family services	1	0.03
Incentive			Community development	1	0.03
Windfall money	19	0.54	Healthcare	1	0.03
Own money	13	0.37	Other	8	0.24
Earned money	1	0.03	Multiple	11	0.33
Multiple	2	0.06	No info	2	0.06

Notes: The dataset comprises 33 papers, covering 35 conceptually distinct studies. Each study is defined as a unique combination of location, experiment type, design, subject, and recipient NGO. Two papers report results from both laboratory and field experiments (Adena and Huck, 2017; Rondeau and List, 2008).

journals (see Table B.1 in the Online Appendix). Descriptive statistics of these papers are presented in Table 1. Interestingly, most experiments (22 out of 33, or 67%) have been conducted in the United States. In terms of subject pools, the modal pools are university students, followed by specific populations (particularly past donors). In terms of NGOs targeted by the experiment, the modal recipient is children and family services, followed by poverty assistance and environmental protection.

On the design side, we observe an approximately equal split between laboratory experiments and natural field experiments, and a recent growth in the use of online experiments. The modal experimental design is to use a between-subjects design.

From the 33 unique papers, we retrieved (and constructed; see Section 2) 151 elasticity estimates, yielding an average of approximately five observations per paper (median: 2; maximum: 18). Most papers employed multiple treatments, with only seven papers using a single treatment.

Regarding price variations, the modal treatment is to adjust the price by 50%, either by using a 1:1 matching or by proposing a 50% rebate on donations. Eleven studies also used a 33% reduction in price (corresponding to a 2:1 matching or 33% rebate). Lastly, a significant number of studies (20) have used multiple prices to compute an elasticity measure. In terms of framing, we have a balanced number of observations between matching and rebate framings, with 80 studies using a matching treatment and 71 using a rebate treatment (21 of which use

TABLE 2: Summary statistics of reported elasticities.

Type	N	Mean	SD	Q1	Median	Q3	Min	Max
Checkbook	150	−1.00	1.73	−1.23	−0.36	−0.07	−7.33	1.77
Net	107	−0.83	1.80	−0.83	−0.23	0.13	−7.33	0.97
Total	97	−1.11	1.52	−1.67	−0.67	−0.20	−6.20	1.77

Notes: Checkbook elasticity represents the initial amount contributed by the donor, before applying either the match or the rebate. Total elasticity refers to the money received by the charity, and the net donation is the amount effectively paid by the donor, once a rebate has been taken into account.

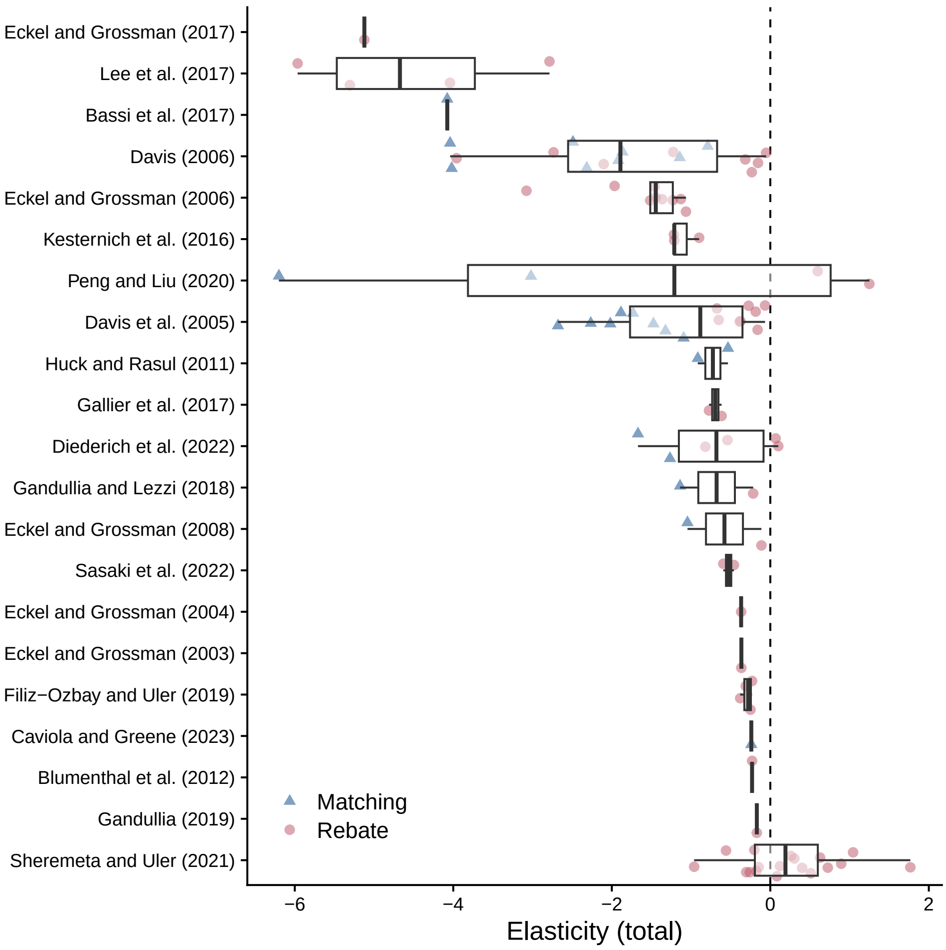

FIGURE 2: Distribution of total donation elasticities. *Notes*: Figures B.1 and B.2 in the Online Appendix show the distributions of checkbook donation elasticity and net donation elasticity, respectively.

an explicit tax framing).

Descriptive statistics on elasticities are presented in Table 2. The sample mean of the checkbook donation elasticity is −1.00 (SD = 1.73), with values ranging from −7.33 to 1.77. For total donations, the elasticity is, on average, stronger, with an average of −1.11 (SD = 1.52). Net donations have a mean elasticity of −0.83 (SD = 1.80). Total donation elasticity estimates are plotted in Figure 2. Interestingly, we observe considerable variation both between and within papers in reported elasticities.

4 Results

We structure the section in three steps. First, we estimate the average price elasticity reported in the literature to obtain an initial sense of its overall magnitude. Second, we assess the presence of publication bias and re-estimate the average elasticity after correcting for it. Finally, we compare the elasticity of charitable giving under matching and rebate schemes using meta-regression analyses.

4.1 Meta-Analytic Average Elasticities

We begin by providing a meta-analytic estimate of the average elasticity reported in the literature, offering the current best answer to the question: What is the overall tendency of price elasticity observed in charitable giving experiments?

To do so, we start with specifying a random-effects model following DerSimonian and Laird (1986):

$$e_i = \overline{e}_i + \varepsilon_i = e_0 + \mu_i + \varepsilon_i, \tag{2}$$

where $\varepsilon_i \sim \mathcal{N}(0, se_i^2)$ is a sampling variation of e_i as an estimate of $\overline{e}_i$, and the observation-specific "true" elasticity $\overline{e}_i$ is decomposed into e_0 (the overall mean) and the sampling variation μ_i. It is further assumed that $\mu_i \sim \mathcal{N}(0, \tau^2)$, where τ^2 is the genuine heterogeneity, beyond the mere sampling variance, that must be estimated. The random-effects estimate of e_0 is calculated by the weighted average of individual estimates, where the weight is given by $w_i = 1/(se_i^2 + \hat{\tau}^2)$ and $\hat{\tau}^2$ is the estimate of τ^2.

Note that our dataset includes *statistically dependent* estimates of $\overline{e}_i$, as many studies included in the meta-analysis report multiple elasticity estimates. To account for this within-study dependence, we use cluster-robust variance estimation to account for the correlation of estimates among each study (Hedges et al., 2010).

We also apply three-level modeling to handle statistically dependent estimates (Van den Noortgate et al., 2013). Let e_{pi} denote the ith estimate of e from paper p. The first level is $e_{pi} = \overline{e}_{pi} + \varepsilon_{pi}$, where $\overline{e}_{pi}$ is the "true" price elasticity and $\varepsilon_{pi} \sim \mathcal{N}(0, se_{pi}^2)$ for the ith estimate in paper p. The second level is $\overline{e}_{pi} = \overline{e}_p + \mu_{pi}^{(2)}$, where $\overline{e}_p$ is the average price elasticity in paper p and $\mu_{pi}^{(2)} \sim \mathcal{N}(0, \tau_{(2)}^2)$. Finally, the third level is $\overline{e}_p = e_0 + \mu_p^{(3)}$, where e_0 is the population average of e and $\mu_p^{(3)} \sim \mathcal{N}(0, \tau_{(3)}^2)$. These equations are combined into a single model:

$$e_{pi} = e_0 + \mu_{pi}^{(2)} + \mu_p^{(3)} + \varepsilon_{pi}. \tag{3}$$

We estimate a random-effects model (2) and a multi-level model (3) for each type of reported elasticities (checkbook, net, and total) separately. Results are presented in Table 3, and visualized in Figure 3 for total donation elasticities and Figures B.3 and B.4 for checkbook giving and net giving in the Online Appendix.

Table 3: Meta-analytic average elasticity.

	RE			ML		
	(1) Checkbook	(2) Net	(3) Total	(4) Checkbook	(5) Net	(6) Total
$\widehat{e}_0$	-0.883^{*}	-0.701	-1.046^{*}	-0.795^{***}	-0.871^{***}	-1.247^{***}
$SE(\widehat{e}_0)$	(0.369)	(0.424)	(0.356)	(0.217)	(0.273)	(0.303)
95% CI	[−1.676, −0.090]	[−1.622, 0.221]	[−1.871, −0.221]	[−1.237, −0.352]	[−1.429, −0.313]	[−1.879, −0.614]
τ^2	2.129	2.269	1.969			
I^2	99.98	99.986	99.78			
$\tau^2_{(2)}$				0.52	0.126	0.942
$\tau^2_{(3)}$				1.281	2.102	1.447
I^2_{within}				28.87	5.666	39.363
I^2_{between}				71.107	94.319	60.456
Num. clusters	33	30	21	33	30	21
Num. obs.	150	107	97	150	107	97

Notes: (1-3) Benchmark random-effects model (equation (2)). (4-6) Multi-level model (equation (3)). Standard errors are clustered at the paper level. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.005$.

We find that the meta-analytical average elasticity is -1.046 for total donation, with a 95% confidence interval of $[-1.871, -0.221]$. This parameter is policy-relevant, as it implies that the total amount received by charities varies significantly with donation prices. Reducing donation prices (through tax rebates, for example) substantially raises donations. For checkbook elasticity, the average price elasticity is -0.883 (95% CI $[-1.676, -0.090]$), while for the net donation, these parameters are -0.701 (95% CI $[-1.622, 0.221]$).

We also examine the I^2 statistic (Higgins and Thompson, 2002), which measures the amount of heterogeneity relative to the total amount of variance in the observed effects. Formally, the I^2 statistic is computed by

$$I^2 = \frac{\hat{\tau}^2}{\hat{\tau}^2 + s^2} \times 100,$$

where $\hat{\tau}^2$ is the estimated value of τ^2 and

$$s^2 = \frac{(n-1)\sum_{i=1}^{n} w_i}{(\sum_{i=1}^{n} w_i)^2 + \sum_{i=1}^{n} w_i^2}$$

is the "typical" sampling variance of the observed effect sizes, where $w_i = 1/se_i^2$ and n is the number of observations. We observe that more than 99% of the total variability in estimates is due to between-observation heterogeneity.

Considering the hierarchical structure of our dataset, the multi-level model yields an average elasticity of -1.247 (95% CI $[-1.879, -0.614]$), which is slightly larger than the random-effect model. The heterogeneity measure I^2 adapted to the multi-level specification shows that 60% of the total variance is due to between-paper heterogeneity, 39% is due to within-paper heterogeneity, and the remainder ($< 1\%$) is due to sampling variation.

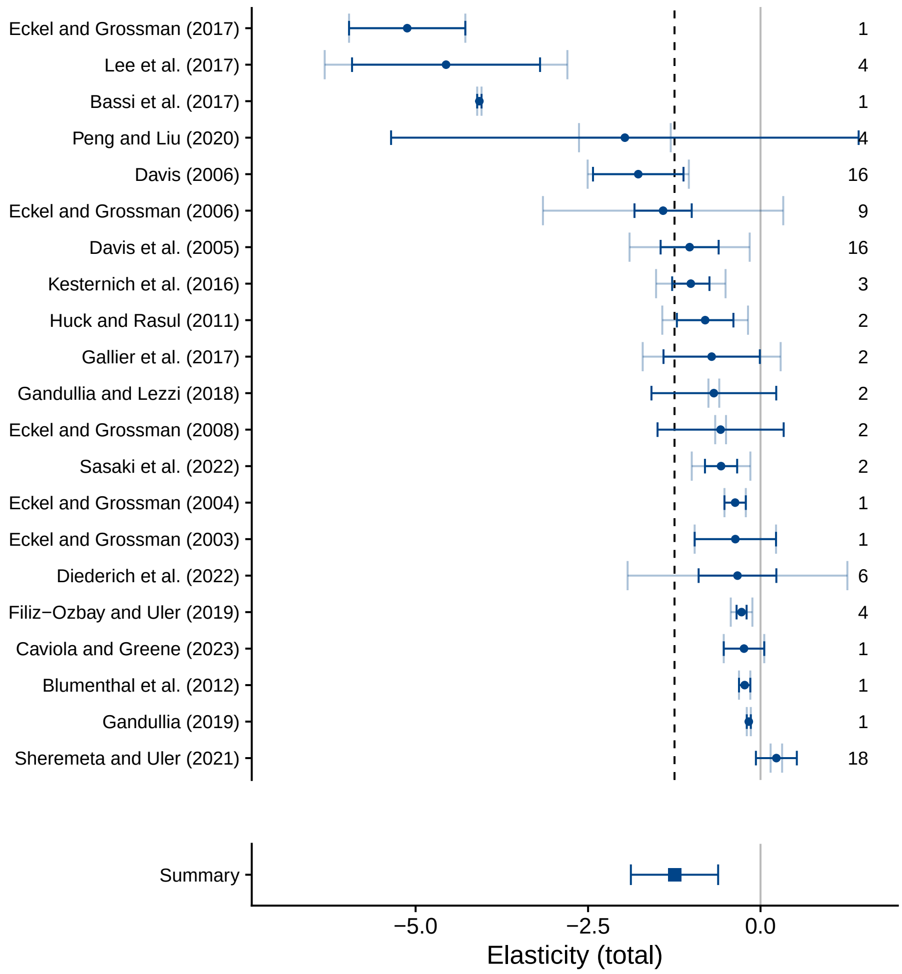

FIGURE 3: Forest plot of paper-level elasticity estimates (total giving). *Notes*: In the top panel, each dot represents the pooled estimate from a study (using a random-effects model), with the dark horizontal lines indicating the corresponding 95% CIs. Light horizontal lines show 95% CIs constructed using the median standard error within each study (Fernández-Castilla et al., 2020). Numbers on the right denote the number of take-up rates reported in each study. The bottom panel shows the average elasticity (and 95% CI) estimated using a multi-level model.

4.2 Publication Bias

A common concern in any meta-analytic synthesis is the possibility that the published evidence may not represent the full universe of conducted studies due to selective reporting or publication of findings. For simplicity, we refer to this distortion of evidence collectively as publication bias. Publication bias can manifest in various forms. The typical form of bias inflates effect sizes by favoring statistically significant or positive estimates that reject some null hypothesis (Andrews and Kasy, 2019; Brodeur et al., 2016, 2020; Chopra et al., 2024). In the context of charitable-giving research, this concern is particularly salient: estimates of price elasticity may serve as inputs for policy design or fundraising strategies. Consequently, studies finding weak or insignificant price responsiveness may be less likely to appear in published outlets, potentially distorting the empirical distribution used in meta-analytic estimation.

Funnel plots, shown in Figure 4, are often used as a graphical tool to examine bias (Egger

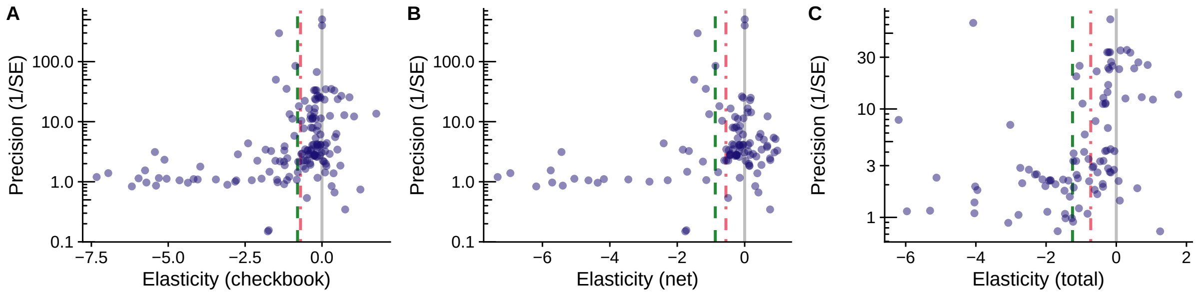

FIGURE 4: Relationship between reported/calculated elasticities and their corresponding precision ($1/SE$). *Notes*: The y-axis is shown on a log scale to improve visual clarity. The vertical green dashed lines represent multi-level estimates reported in columns (4)-(6) in Table 3. The vertical red dot-dashed lines represent limit meta-analysis results reported in Table 4.

et al., 1997; Stanley and Doucouliagos, 2010). In particular, asymmetry in the funnel shape is commonly interpreted as evidence consistent with publication bias, as imprecise studies tend to be missing when their estimated effects are close to zero or in an unexpected direction. Statistically, such patterns can be formally assessed using the FAT–PET approach, which evaluates whether effect sizes systematically vary in relation to their standard errors (Stanley and Doucouliagos, 2014). However, funnel plots and related tests have important limitations: asymmetry may arise from genuine heterogeneity rather than selective reporting, and the tests have low power in small meta-analyses.

To address these limitations, we adopt limit meta-analysis (LMA; Rücker et al., 2011), a method designed to correct for publication bias while explicitly modeling between-study heterogeneity within a random-effects framework. LMA models the dependence between a study's effect size and its precision by regressing effect sizes on a transformation of the study-specific standard error that incorporates the estimated between-study variance (τ^2):

$$e_i = \beta + \sqrt{se_i^2 + \tau^2}\,(\alpha + \epsilon_i)\,, \tag{4}$$

where e_i is the ith elasticity estimate, se_i is its standard error, and ϵ_i is a standard-normal error term. This model yields two primary parameters: a mean effect (β) and a publication bias term (α), the latter representing the degree to which less precise studies deviate from the estimates of large studies. The method then computes a bias-adjusted pooled effect by extrapolating the fitted model to the hypothetical situation of infinite precision (i.e., as the standard error goes to zero). The resulting limit estimate $\bar{e}_{\text{lim}} = \beta + \alpha\tau$ represents the effect if there were no publication bias.[2]

Results, presented in Table 4, indicate that there is evidence of some publication bias.

[2]While the limit meta-analysis offers advantages (e.g., it explicitly models between-study variance, unlike FAT-PET), some caveats remain. Most importantly, it assumes a specific functional relationship between effect size and precision (via the term $\sqrt{se_i^2 + \tau^2}$). If the true mechanism of publication bias is more complex (e.g., selection dependent on p-values or effect size in non-linear ways), the model may mis-specify the bias. For additional contemporary approaches to correcting publication bias, see Irsova et al. (2024).

Table 4: Meta-analytic average elasticity with publication bias adjustment.

	(1) Checkbook	(2) Net	(3) Total
Bias-adjusted estimate ($\overline{e}_{\text{lim}}$)	-0.699^{***}	-0.556^{***}	-0.728^{***}
$SE(\overline{e}_{\text{lim}})$	(0.137)	(0.163)	(0.181)
95% CI	[−0.967, −0.431]	[−0.876, −0.236]	[−1.082, −0.374]
Publication bias (α)	-2.342^{***}	-1.950^{**}	-4.732^{***}
$SE(\alpha)$	(0.659)	(0.714)	(1.503)
Num. obs	150	107	97

Notes: Limit meta-analysis (equation (4)) with the dependent variables: (1) Checkbook giving elasticity (given by subjects); (2) net elasticity (actually paid by subjects); (3) total elasticity (received by charities). *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.005$.

Table 5: Price-elasticity of giving: matching vs. rebates.

	(1) Checkbook	(2) Net	(3) Total
Matching	−0.322	−0.621	-1.409^{*}
	(0.572)	(0.334)	(0.373)
Constant	−0.587	−0.332	-0.868^{*}
	(0.369)	(0.388)	(0.320)
Num. clusters	33	30	21
Num. obs.	150	107	97

Notes: The dependent variables are: (1) Checkbook giving elasticity (given by subjects); (2) net elasticity (actually paid by subjects); (3) total elasticity (received by charities). Standard errors, clustered at the paper level, are reported in parentheses. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.005$.

Indeed, the parameter α is statistically significantly negative ($p < 0.01$ for all three outcomes), indicating that studies with a stronger price elasticity (larger in absolute terms) are often those with smaller precision (larger variance of the estimator). Because of this, correcting for publication bias pushes the meta-analytic elasticities toward 0, but the magnitude of the correction is not dramatic: for the three measures of elasticities, the non-bias-adjusted meta-analytical means (Table 3, columns (1) to (3)) fall within the 95% confidence intervals of the bias-adjusted estimates.

4.3 Comparing Matching and Rebates

We then estimate whether the estimated price elasticities differ between matching and rebate treatments. Recall that the hypotheses of Eckel and Grossman (2003) are that 1) the elasticity of checkbook giving should be larger in absolute value under rebates than under matching; 2) and 3) the price elasticities under both schemes should be identical for net and total giving.

In Table 5, we present the meta-analytic estimates of differences in elasticities between matching and rebates. The meta-analytical results substantially differ from these predictions. The first result is that there is no statistically significant difference between the estimated price elasticity of checkbook donations in matching and rebate ($p = 0.589$). In fact, opposite to the predicted direction, the elasticity under matching is, if anything, stronger in absolute value than that of rebate. Again, contrary to the hypotheses, the elasticity of net and total giving is stronger under matching than rebate; the difference is statistically significant for total donations ($p = 0.031$), although not for net donations ($p = 0.163$). These results, while contradictory with theoretical patterns, align with the experimental results of Eckel and Grossman (2003).

For policy, the estimated elasticity of total donations implies that although lowering the price of giving substantially increases the funds charities receive, rebate schemes exert a much smaller effect on total donations. Tables B.3 and B.4 in the Online Appendix, which show the meta-analytic average elasticities for rebate and matching schemes separately, confirm this pattern: the average elasticity of total donations is -1.977 (95% CI $[-3.100, -0.853]$) under matching, but only -0.871 (95% CI $[-1.582, -0.160]$) under rebates.

In Table 6, we present heterogeneity analysis with more moderators (price variation, location, type of experiment, and type of incentive). The addition of these additional moderators reinforces the previous result for total and net donations on the difference between matching and rebates, with the matching dummy reaching statistical significance for both types of elasticities when controlling for study-level covariates. The addition of covariates also makes the matching dummy statistically significantly negatively affect checkbook donations, again in a direction opposite to the predicted one.[3]

Regarding the moderating effects of the covariates on the price elasticity of donations, we find that total donations are more price elastic outside the United States. In addition, studies that rely on windfall money, rather than subjects' own money, tend to produce smaller price elasticities.

Furthermore, to examine how these covariates moderate the rebate–matching difference in the elasticity of donations, Table B.6 in the Online Appendix reports specifications that interact the matching dummy with each moderator. The results indicate that the rebate–matching difference is attenuated when moving from laboratory to field or online settings, although it remains persistent. In addition, this difference tends to be more pronounced in studies conducted outside the United States. However, this pattern should be interpreted with caution, as the number of non-U.S. sample reporting total donation elasticities is extremely small (only

[3]Because total donations in matching schemes are a multiple of checkbook giving, it may appear puzzling that the matching coefficient for checkbook donations is nearly identical in magnitude to that for total donations (approximately -1.0). However, this similarity is largely driven by differences in sample size and by the distinct covariate structure of studies that report only checkbook outcomes. Restricting the analysis to the subsample that reports total donation elasticities, as shown in Table B.5 in the Online Appendix, substantially reduces the magnitude of the matching coefficient for checkbook donations, making it statistically indistinguishable from the rebate coefficient.

Table 6: Meta-regression analysis.

	(1) Checkbook	(2) Net	(3) Total
Matching	-1.130^{*}	-1.003^{**}	-1.226^{*}
	(0.295)	(0.196)	(0.264)
d_p	-2.328	-5.038^{***}	0.748
	(2.050)	(0.464)	(0.505)
Location: Non-USA	0.963	0.527^{*}	-2.657^{*}
	(0.372)	(0.108)	(0.490)
Experiment: Field/Online	0.261	-0.149	0.230
	(0.375)	(0.344)	(0.109)
Incentive: Own money	0.318	0.515	-0.117
	(0.293)	(0.230)	(0.299)
Incentive: Other	0.291	0.914	0.623^{**}
	(0.670)	(0.367)	(0.121)
Constant	-1.584	-2.405^{***}	0.014
	(0.850)	(0.310)	(0.256)
Num. clusters	33	30	21
Num. obs.	150	107	97

Notes: The dependent variables are: (1) Checkbook giving elasticity (given by subjects); (2) net elasticity (actually paid by subjects); (3) total elasticity (received by the charity). Standard errors clustered at the paper level are reported in parentheses. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.005$.

five observations), leaving the analysis underpowered to draw firm conclusions.

5 Conclusion

In this paper, we conduct a quantitative meta-analysis of the price elasticity of charitable giving. Drawing on 151 point estimates from 33 primary studies, we estimate a meta-analytic mean price elasticity of total donations of −1.25. Although we detect evidence of publication bias, adjusting for this bias does not materially change our conclusions.

Our primary contribution to the literature lies in comparing price elasticities under matching and rebate mechanisms. This comparison is motivated by a discrepancy between price-equivalence predictions—which suggest no difference in the price elasticity of total donations between matching and rebate—and empirical findings. Consistent with the seminal work by Eckel and Grossman (2003), we find that matching schemes yield substantially more negative price elasticities of total donations than rebate schemes, at −1.98 versus −0.87. Whereas Eckel and Grossman (2003) reported roughly a threefold difference in elasticities, our meta-analytic estimate suggests that the gap is closer to twofold when synthesizing the broader evidence base.

Beyond establishing the non-equivalence of rebate and matching schemes, our meta-analysis reveals substantial heterogeneity in the magnitude of price elasticities across studies. Recent theoretical work helps account for this pattern. Hungerman and Ottoni-Wilhelm (2021) show that in an impure-impact framework, changes in the match rate affect only the cost of generating total impact. In contrast, rebates alter the costs of both total impact and out-of-pocket giving. This structural asymmetry produces fundamentally different donor responses, providing a theoretical foundation for the heterogeneity observed in the literature. Importantly, for assessing external validity, the rebate–matching difference in total donation elasticities is attenuated when moving from laboratory to field settings, but it remains persistent. Additionally, this difference tends to be more pronounced in studies conducted outside the United States. Matching schemes retain a robust performance advantage across diverse settings, reinforcing their practical relevance for fundraising interventions.

Despite the substantive contribution of our analysis, several limitations warrant acknowledgement. First, our review is restricted to experimental studies. We adopt this focus to ensure a relatively homogeneous evidence base, although notable heterogeneity remains even within this subset. Second, we limit our sample to studies that report an explicit and computable price reduction parameter (d_p), even when alternative measures of price elasticity are available, to incorporate this parameter as a moderator. These constraints reduce the size of our sample and may limit the precision of our estimates.

Looking ahead, our results highlight several promising avenues for future research. As new experimental and observational studies accumulate, more comprehensive meta-analyses will be necessary to refine our understanding of how donors respond to changes in price. In particular, studies that expand the geographical scope (e.g., outside the United States), explore alternative incentive mechanisms, or collect richer data on donor characteristics may help to explain some of the heterogeneity we document. Future experimental and theoretical evidence may also help clarify the mechanisms through which matching generates stronger behavioral responses than rebate. Overall, continued efforts to build a broader evidence base will be crucial for clarifying the role of price incentives in shaping charitable behavior.

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Supplementary Online Material

Revisiting the Price Elasticity of Charitable Giving: Meta-Analysis of Tax Incentives and Matching Donations

Gwen-Jiro Clochard Shubham Dey
Shusaku Sasaki Taisuke Imai

Contents

A Data

A.1 Literature Search and Screening

Below, we describe the procedure used to compile a comprehensive list of papers that empirically examine the effects of rebates and matching on charitable donations. To ensure broad coverage of relevant studies, we employed two complementary strategies: (i) a systematic search of academic databases and (ii) a review of reference lists from existing literature reviews.

Systematic database search. We conducted a systematic search for relevant studies using two databases, Web of Science and Google Scholar, employing the following search query:

```
("charitable giving" OR "charitable contributions" OR "fundraising")
                              AND
(    rebate  OR matching OR subsidy
 OR  income  OR tax      OR "price incentive")
```

The search query was designed to capture well-known experimental studies, aiming to balance specificity with inclusiveness. The Web of Science search returned 860 papers, while Google Scholar yielded the first 996 relevant results. After removing duplicates, we obtained a set of 1,578 unique papers. Following two rounds of screening—first based on titles and abstracts, and then on a more detailed review—we identified 33 primary studies that form the basis of our meta-analysis.

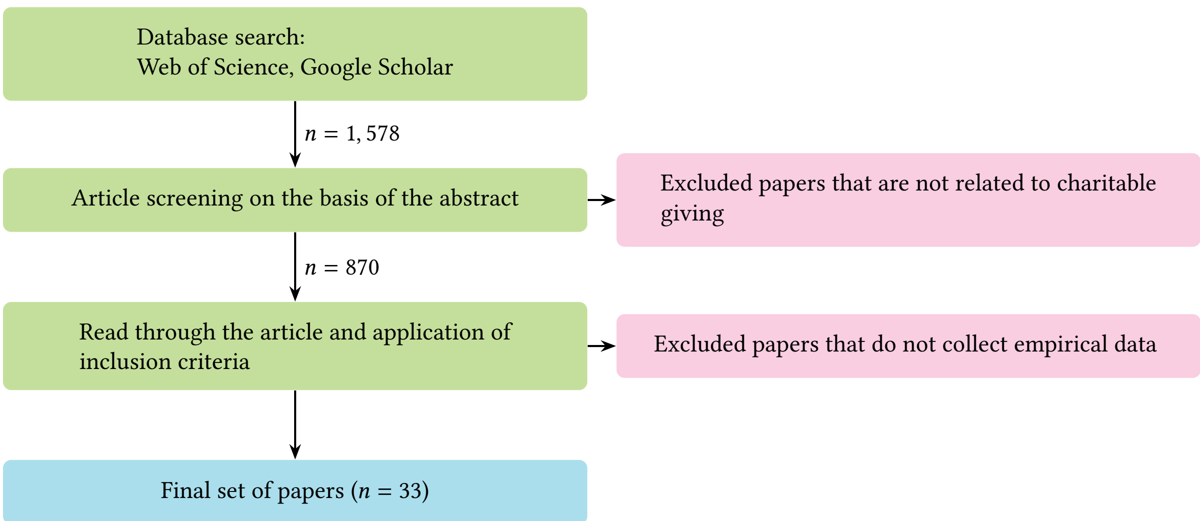

FIGURE A.1: Literature search and screening. *Notes*: The list of 33 papers included in the meta-analysis is available in Section C below.

A.2 Coded Variables

TABLE A.1: List of coded variables.

Variable	Description
Article meta data	
`author_lastname`	Last name(s) of the author(s)
`author_firstname`	First name(s) of the author(s)
`title`	Title of the paper
`published`	= 0 if unpublished; =1 if published
`year`	Year of publication (or WP version if unpublished)
`journal`	Journal name
`doi`	Article DOI
Treatment	
`matching`	=1 if the study is about matching donations
`rebate`	=1 if the study is about a rebate
`tax_framed`	=1 if framed as taxation (if rebate)
Implementation	
`year_conducted`	Year the experiments were run / data collected
`location_country`	Where the study was run (country)
`location_continent`	Where the study was run (continent)
`location_asia`	=1 if study conducted in Asia
`location_europe`	=1 if study conducted in Europe
`location_africa`	=1 if study conducted in Africa
`location_americas`	=1 if study conducted in Americas
`location_oceania`	=1 if study conducted in Oceania
`n_total`	Total number of participants in the experiment
`n_study`	Number of participants in the treatment
Design	
`exp_lab`	=1 if lab experiment
`exp_field_artefactual`	=1 if artefactual field experiment / lab-in-the-field experiment
`exp_field_framed`	=1 if framed field experiment
`exp_field_natural`	=1 if natural field experiment
`exp_online`	=1 if online experiment
`exp_other`	=1 if the type is not covered above
`exp_other_description`	Description of unlisted design
`design_between`	=1 if between-subject design
`design_within`	=1 if within-subject design
Treatment	
`price_100`	=1 if 1:1 matching or 50% rebate is assigned
`price_050`	=1 if 2:1 matching or 33% rebate is assigned
`price_033`	=1 if 3:1 matching or 25% rebate is assigned
`price_025`	=1 if 4:1 matching or 20% rebate is assigned
`price_020`	=1 if 5:1 matching or 20% rebate is assigned
`price_other`	Other % of rebate/matching

Continued on next page.

Variable	Description
Subject	
subject_uni	=1 if subjects are university students / staff members
subject_online_pool	=1 if subjects are from online pools
subject_specific	=1 if specific groups of people are recruited
subject_specific_description	Description of the subject population
subject_general	=1 if no restriction in the population
NGO	
recipient_known	=1 if the NGO is mentioned
recipient_ngo_education	=1 if NGO is about education
recipient_ngo_environment	=1 for environment
recipient_ngo_poverty	=1 for poverty ngo
recipient_ngo_children	=1 for children and family services
recipient_ngo_community	=1 for community development ngo
recipient_ngo_health	=1 for healthcare related ngo
recipient_ngo_other	=1 for other NGO
recipient_ngo_other_description	Description of the unlisted NGO
recipient_compulsory	=1 if a recipient is fixed
recipient_noncompulsory	=1 if subjects can choose a recipient among several
Incentives	
incentivized	=1 if incentivized with real money
incentivized_money_windfall	=1 if the money is provided by the experimenter without effort
incentivized_money_effort	=1 if the money is earned from the experimenter
incentivized_money_own	=1 if subjects have to donate their own money
incentivized_other	=1 if other form of incentives
Outcome measures	
elasticity_present	=1 if there is a measure of the elasticity of donation
elasticity_checkbook	Elasticity estimate for checkbook donation
se_elasticity_checkbook	Standard error of checkbook donation elasticity estimate
elasticity_net	Elasticity estimate for net donation
se_elasticity_net	Standard error of net donation elasticity estimate
elasticity_total	Elasticity estimate for total donation
se_elasticity_total	Standard error of total donation elasticity estimate
d_price	Price variation d_p

A.3 Imputation of Elasticities

When an elasticity was reported in the paper, we used it directly. If it was not reported, we imputed the elasticity using the reported treatment effects, and when those were unavailable, we used the means of the control and treatment groups. This procedure can be summarized as follows:

$$e^{\text{imp}} = \frac{\overline{D}_{\text{diff}}}{\overline{D}_{\text{control}} \times d_p}$$

$$SE(e^{\text{imp}}) = \frac{SD_{\text{pooled}}}{\overline{D}_{\text{control}} \times |d_p|}$$

where $\overline{D}_{\text{treatment}}$ and $\overline{D}_{\text{control}}$ denote mean donations in the treatment and control groups, SD_{pooled} denotes the pooled standard deviation, and d_p represents the price variation between the two conditions.

B Additional Figures and Tables

Table B.1: List of journals.

Journal	N	Share
American Economic Review	1	0.03
Ecological Economics	1	0.03
Economics Letters	2	0.06
European Economic Review	1	0.03
Experimental Economics	5	0.16
Games and Economic Behavior	1	0.03
Japanese Economic Review	1	0.03
Journal of Behavioral and Experimental Economics	3	0.09
Journal of Public Economics	6	0.19
Journal of the European Economic Association	2	0.06
Judgment and Decision Making	2	0.06
Management Science	2	0.06
National Tax Journal	1	0.03
Nonprofit and Voluntary Sector Quarterly	1	0.03
Science Advances	1	0.03
Southern Economic Journal	2	0.06

Table B.2: Characteristics of the observations.

	All		Checkbook		Net		Total	
	N	Share	N	Share	N	Share	N	Share
Num. obs.	151	1.00	150	1.00	107	1.00	97	1.00
Treatment								
Matching	80	0.53	79	0.53	79	0.74	26	0.27
Rebate	71	0.47	71	0.47	28	0.26	71	0.73
Location								
Americas	118	0.78	117	0.78	79	0.74	83	0.86
Europe	17	0.11	17	0.11	12	0.11	8	0.08
Asia	9	0.06	9	0.06	9	0.08	6	0.06
Multiple	7	0.05	7	0.05	7	0.07		
Type of experiment								
Laboratory	97	0.64	97	0.65	65	0.61	72	0.74
Natural field	32	0.21	32	0.21	23	0.21	13	0.13
Online	22	0.15	21	0.14	19	0.18	12	0.12
Incentive								
Windfall money	95	0.63	94	0.63	78	0.73	60	0.62
Own money	30	0.20	30	0.20	21	0.20	11	0.11
Earned money	24	0.16	24	0.16	6	0.06	24	0.25
Multiple	2	0.01	2	0.01	2	0.02	2	0.02

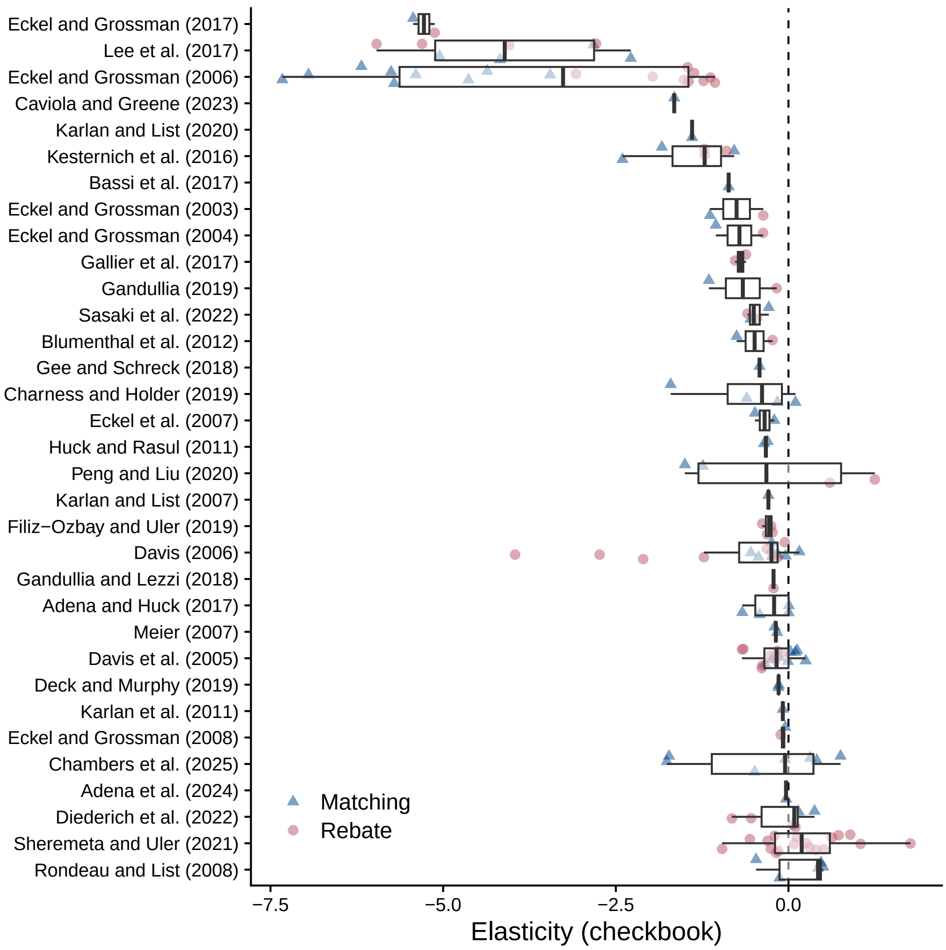

FIGURE B.1: Distribution of total donation elasticities.

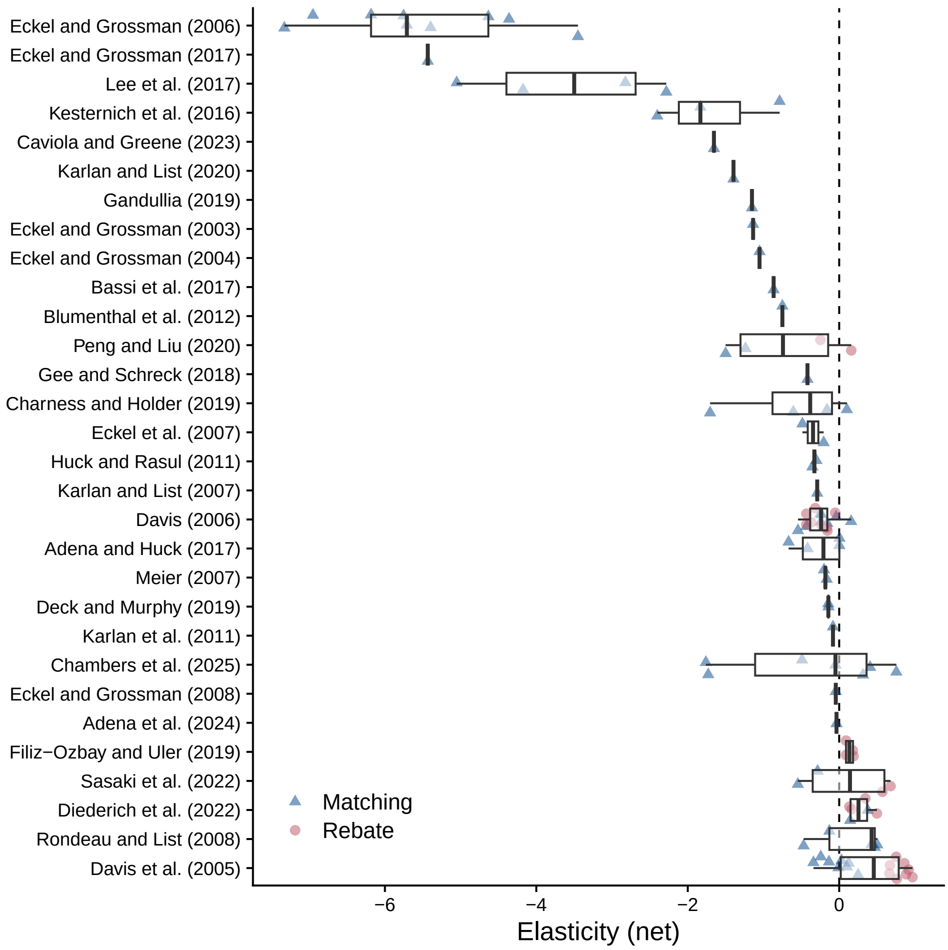

Figure B.2: Distribution of net donation elasticities.

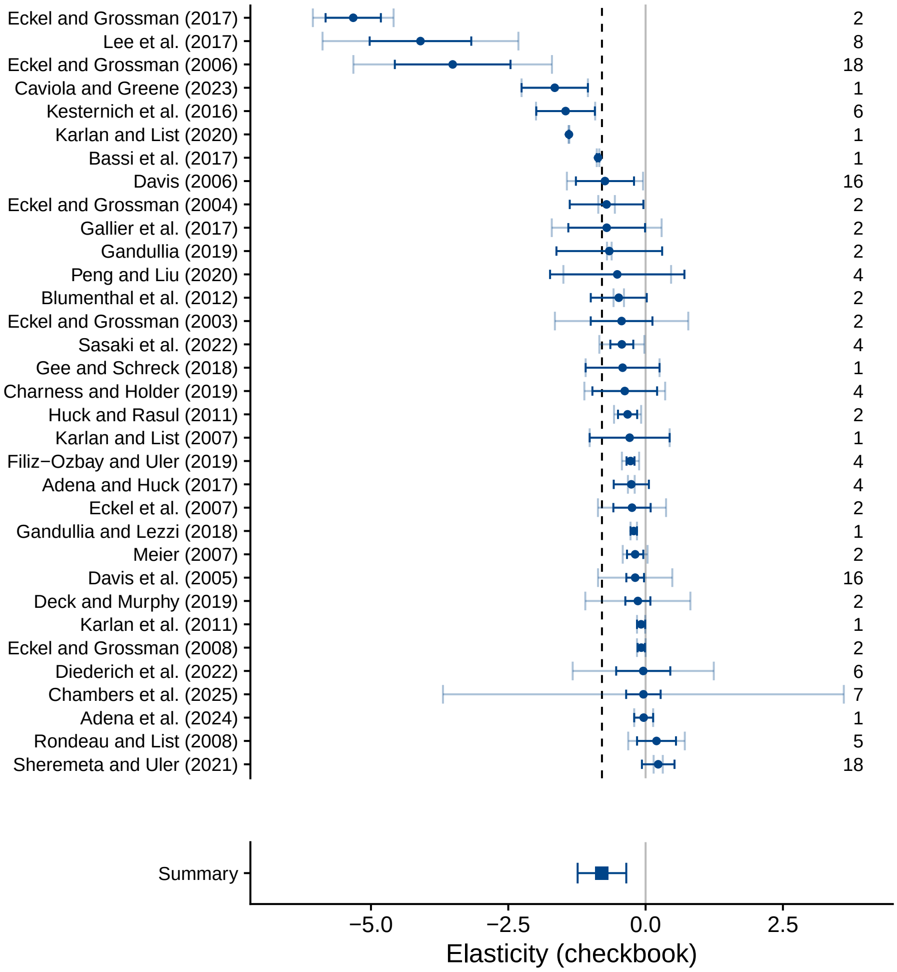

FIGURE B.3: Forest plot of paper-level elasticity estimates (checkbook giving). *Notes*: Each dot represents the pooled estimate from a study (using a random-effects model), with the dark horizontal lines indicating the corresponding 95% CIs. Light horizontal lines show 95% CIs constructed using the median standard error within each study (Fernández-Castilla et al., 2020). Numbers on the right denote the number of take-up rates reported in each study. Numbers on the right denote the number of take-up rates reported in each study. The bottom panel shows the average elasticity (and 95% CI) estimated using a multilevel model.

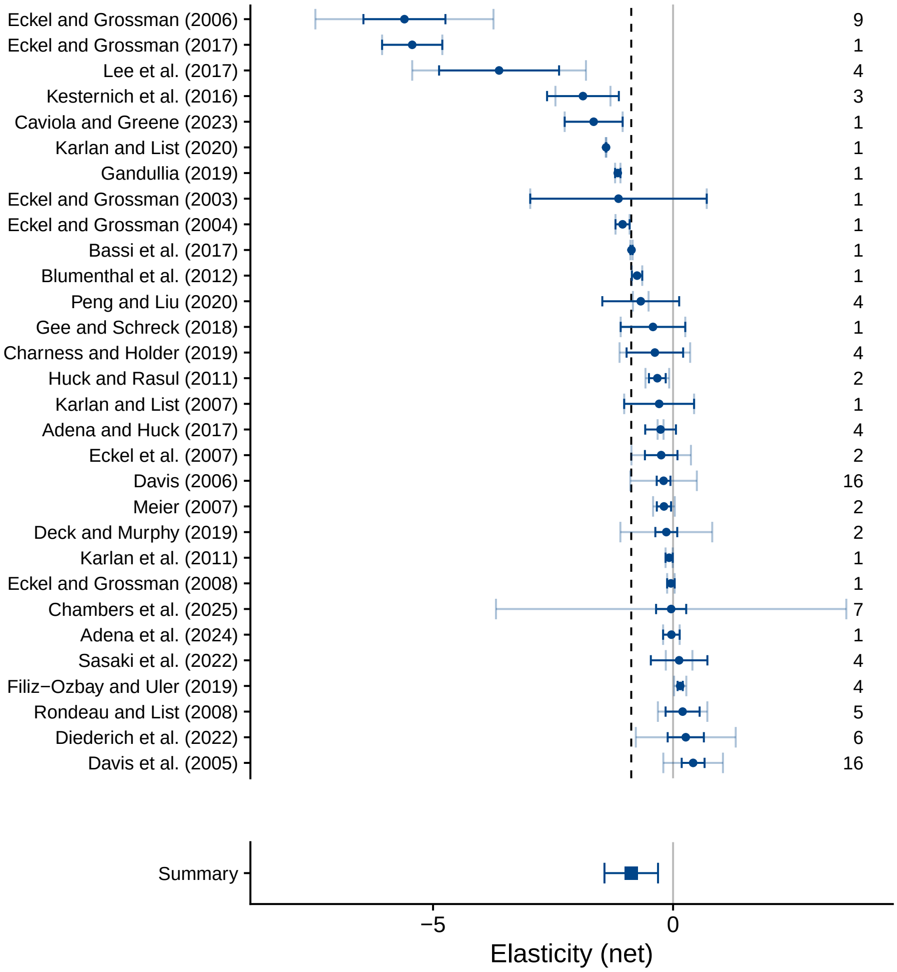

Figure B.4: Forest plot of paper-level elasticity estimates (net giving). *Notes*: Each dot represents the pooled estimate from a study (using a random-effects model), with the dark horizontal lines indicating the corresponding 95% CIs. Light horizontal lines show 95% CIs constructed using the median standard error within each study (Fernández-Castilla et al., 2020). Numbers on the right denote the number of take-up rates reported in each study. Numbers on the right denote the number of take-up rates reported in each study. The bottom panel shows the average elasticity (and 95% CI) estimated using a multilevel model.

Table B.3: Meta-analytic average elasticity: Rebate.

	RE		ML	
	(1) Checkbook/Total	(2) Net	(3) Checkbook/Total	(4) Net
$\widehat{e}_0$	-0.654	0.253	-0.871^{*}	0.283
$SE(\widehat{e}_0)$	(0.372)	(0.234)	(0.337)	(0.167)
95% CI	$[-1.539, 0.231]$	$[-0.397, 0.903]$	$[-1.582, -0.160]$	$[-0.147, 0.712]$
Num. clusters	18	6	18	6
Num. obs.	71	28	71	28

Notes: Checkbook and total donation elasticities are equivalent under the rebate schemes. (1-2) Benchmark random-effects model (equation (2)). (3-4) Multi-level model (equation (3)). Standard errors are clustered at the paper level. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.005$.

Table B.4: Meta-analytic average elasticity: Matching.

	RE		ML	
	(1) Checkbook/Net	(2) Total	(3) Checkbook/Net	(4) Total
$\widehat{e}_0$	-1.102	-2.055^{***}	-0.974^{***}	-1.977^{***}
$SE(\widehat{e}_0)$	(0.525)	(0.312)	(0.276)	(0.484)
95% CI	$[-2.214, 0.011]$	$[-2.939, -1.171]$	$[-1.541, -0.408]$	$[-3.100, -0.853]$
Num. clusters	29	9	29	9
Num. obs.	79	26	79	26

Notes: Checkbook and net donation elasticities are equivalent under the rebate schemes. (1-3) Benchmark random-effects model (equation (2)). (4-6) Multi-level model (equation (3)). Standard errors are clustered at the paper level. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.005$.

Table B.5: Meta-regression analysis: Subsample of studies with total donation elasticities.

	(1) Checkbook	(2) Total
Matching	-0.157	-1.226^{*}
	(0.188)	(0.264)
d_p	0.630	0.748
	(0.700)	(0.505)
Location: Non-USA	-0.879^{*}	-2.657^{*}
	(0.131)	(0.490)
Experiment: Field/Online	0.269	0.230
	(0.147)	(0.109)
Incentive: Own money	0.215	-0.117
	(0.255)	(0.299)
Incentive: Other	0.695^{*}	0.623^{**}
	(0.191)	(0.121)
Constant	-0.132	0.014
	(0.363)	(0.256)
Num. clusters	21	21
Num. obs.	96	97

Notes: The dependent variables are: (1) Checkbook giving elasticity (given by subjects); (2) total elasticity (received by the charity). We restrict the sample to observations for which total donation elasticities are available. Cf. Table 6. Standard errors clustered at the paper level are reported in parentheses. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.005$.

Table B.6: Meta-regression analysis: Alternative model specification.

	(1) Checkbook	(2) Net	(3) Total
Matching	−1.330	-1.086^{*}	-1.645^{***}
	(0.793)	(0.347)	(0.127)
Matching × Location: Non-USA	1.673	0.433	-2.564^{**}
	(0.530)	(0.189)	(0.177)
Matching × Experiment: Field/Online	0.239	−0.711	0.808^{*}
	(0.817)	(0.523)	(0.155)
d_p	−2.222	-5.003^{***}	0.901^{*}
	(2.234)	(0.408)	(0.060)
Location: Non-USA	−0.689	0.100	−0.421
	(0.521)	(0.177)	(0.089)
Experiment: Field/Online	0.148	0.516	0.128
	(0.056)	(0.514)	(0.059)
Incentive: Own money	0.251	0.549	−0.204
	(0.405)	(0.194)	(0.160)
Incentive: Other	0.184	0.312	0.595^{***}
	(0.439)	(0.592)	(0.052)
Constant	−1.410	-2.299^{***}	0.138
	(1.106)	(0.244)	(0.067)
Num. clusters	33	30	21
Num. obs.	150	107	97

Notes: The dependent variables are: (1) Checkbook giving elasticity (given by subjects); (2) net elasticity (actually paid by subjects); (3) total elasticity (received by the charity). Standard errors clustered at the paper level are reported in parentheses. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.005$.

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