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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 137 elasticity estimates from 26 experimental papers and synthesize them using random-effects and multilevel models. Charitable giving is highly price-responsive: the pooled meta-analytic mean elasticity of total donations is −1.75, 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 (−2.44) than under rebate (−0.73), 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. Consider 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. The donor's out-of-pocket cost per dollar received by the charity, the *price of giving*, p, is therefore $\$50/\$100 = 0.50$. Now consider a 50% rebate: the individual donates \$100 and receives a \$50 refund, yielding the same out-of-pocket cost of \$50 and the same total contribution of \$100, so the price of giving is again $p = 0.50$. Because the two schemes produce the same price of giving, they are economically equivalent.

More generally, under a rebate with rate r, the price of giving is $p = 1-r$. Under a matching scheme with matching rate m, i.e., the amount added by the matcher per dollar donated, the price of giving is $p = 1/(1+m)$. We adopt the convention that an X:1 match denotes a scheme in which the matching grant adds one dollar for every X dollars contributed by the donor, so that $m = 1/X$. For example, in a 2:1 match, every \$2 from the donor brings \$1 from the matching grant, yielding a matching rate of $m = 1/2$. The two mechanisms yield the same price of giving whenever the matching and rebate rates satisfy:

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

A 2:1 match ($m = 1/2$) thus corresponds to approximately a 33% rebate ($p = 0.67$), and a 4:1 match ($m = 1/4$) corresponds to a 20% rebate ($p = 0.80$).

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, defined as 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 total giving 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 the effects of rebate and matching schemes on 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 26 pri-

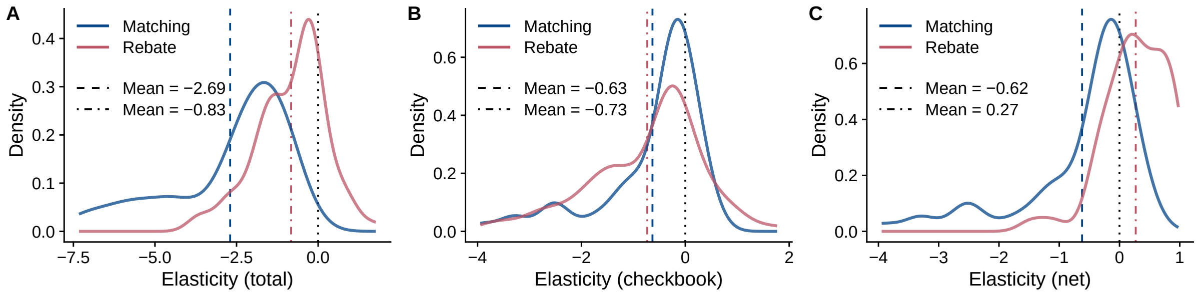

FIGURE 1: Distributions of price elasticities of charitable donations under rebate and matching schemes. (A) Total donation ($N = 134$). (B) Checkbook donation ($N = 132$). (C) Net donation ($N = 111$). *Notes*: Checkbook elasticity represents the amount contributed by the donor, before applying either the match or the rebate. Total elasticity refers to the amount of money received by the charity, and the net donation is the amount effectively paid by the donor after a rebate is taken into account. The kernel density estimate of the distribution is displayed, computed with a Gaussian kernel and bandwidth selected using Silverman's rule of thumb.

mary studies and extract (or compute) 137 measures of price elasticities. Figure 1 provides an initial overview of the evidence in the literature. The unweighted distributions of elasticities reveal substantial heterogeneity and 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 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 -1.745 (95% CI $[-2.332, -1.158]$), 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, albeit with reduced magnitude.

Turning to the comparison between matching and rebate schemes, we find that experimental participants are more responsive to price changes under matching schemes than under rebates. The meta-analytic average elasticity of total donations is -2.440 (95% CI $[-3.215, -1.665]$) under matching, but only -0.728 (95% CI $[-1.163, -0.294]$) under rebates. We further find that the rebate-matching difference is attenuated when moving from laboratory to field settings, although it persists. Apart from this interaction, we do not identify other moderators that consistently account for variation in the reported elasticities

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 (2026) 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) and Salmon (2024) offer quantitative meta-analyses of the tax-price elasticity of giving, while Hung et al. (2025) provide a broader meta-analysis of the price of giving that incorporates nonprofit cost components, such as fundraising and administrative expenses, as well as tax deductibility. None of these quantitative meta-analyses, however, directly compares rebate and matching incentives. Epperson and Reif (2019) present a comprehensive review focused on matching subsidies and discuss theoretical contrasts with rebate mechanisms, but without conducting a statistical meta-analysis of effect sizes. Our study complements existing evidence syntheses by providing the first quantitative meta-analysis to directly compare rebate and matching schemes and assess their respective effects on price elasticities within 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 data. 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 exogenously vary the price of giving. 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 selected only papers in which 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 selected only papers in which donations were an outcome, so 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 137 point estimates from 26 papers

Table 1: Price of giving under rebate and matching mechanisms.

Mechanism	Rate	Price of giving (p)	$d_p = p - 1$
50% rebate	$r = 0.50$	$1 - r = 0.50$	-0.50
33% rebate	$r = 0.33$	$1 - r = 0.67$	-0.33
25% rebate	$r = 0.25$	$1 - r = 0.75$	-0.25
20% rebate	$r = 0.20$	$1 - r = 0.80$	-0.20
1:1 match	$m = 1$	$1/(1 + m) = 0.50$	-0.50
2:1 match	$m = 1/2$	$1/(1 + m) = 0.67$	-0.33
3:1 match	$m = 1/3$	$1/(1 + m) = 0.75$	-0.25
4:1 match	$m = 1/4$	$1/(1 + m) = 0.80$	-0.20

Notes: p denotes the out-of-pocket cost to the donor per dollar of donation received by the charity. In the absence of any subsidy, $p = 1$. For rebates (tax deductions) at rate r, the donor pays 1 and receives r back, so $p = 1 - r$. For matching at rate m, the donor pays 1 and the charity receives $1 + m$, so $p = 1/(1 + m)$. The price change is $d_p = p - 1$.

(28 conceptually distinct studies) for the analysis. The details of the search and selection procedure are summarized in Online Appendix A.1, together with a PRISMA flow diagram (Figure A.1). The list of primary studies is presented in Online Appendix D.

2.2 Data Construction

We constructed the dataset of our meta-analysis by coding the relevant information we gathered from the 26 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. As defined above, the price of giving p equals $1 - r$ for rebates and $1/(1 + m)$ for matching, where r is the rebate rate and m is the matching rate. The price variation is $d_p = p - 1$, so that $d_p = -r$ for rebates and $d_p = -m/(1 + m)$ for matching. Equivalent rebate and matching schemes share the same d_p: for example, a 33% rebate and a 2:1 match ($m = 1/2$) both yield $d_p = -0.33$. Further examples are provided in Table 1.

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:[1]

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

[1] As a robustness check, Online Appendix C reports all analyses using an alternative elasticity construction procedure. Instead of prioritizing reported elasticities, we first compute elasticities from the reported means and standard deviations whenever feasible, relying on the reported elasticity only when such computation is not possible.

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

We gathered three types of price elasticities of donations: checkbook donations, total donations, and net donations.[2] A checkbook donation refers to the amount paid by the donor. The total donation is the amount received by the charity, while the net donation is the final amount for the individual after deducting any 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 place greater 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 variables describing 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.

3 Overview of the Data

In total, 26 unique experimental papers, covering 28 conceptually different studies, were identified. All of these papers had been published across 12 peer-reviewed journals (see Table B.1 in the Online Appendix). Descriptive statistics of these papers are presented in Table 2. Most experiments (20 out of 28, or 71%) 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). Among NGOs targeted by the experiment, the most common classification is multiple recipient types (39%), followed by other types of NGOs (32%). The remaining studies are scattered across categories such as environment, poverty, children and family services, community development, and education, with no single category represented by more than two studies. The specific combinations of NGO types used by the 11 multi-recipient studies vary considerably, with nearly every study assembling a different set (see Figure B.1 in the Online Appendix).

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

From the 26 unique papers, we retrieved (and constructed; see Section 2) 137 elasticity

[2] 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 2: Characteristics of the studies.

	N	Share		N	Share
Type of experiment			*Location of the study*		
Laboratory	12	0.43	United States	20	0.71
Natural field	11	0.39	Europe	5	0.18
Online	5	0.18	Asia	3	0.11
Design			*Recipient type*		
Between subject	22	0.79	Environment	2	0.07
Within subject	5	0.18	Poverty	2	0.07
Mixed	1	0.04	Children and family services	1	0.04
Incentive			Community development	1	0.04
Windfall money	15	0.54	Education	1	0.04
Own money	10	0.36	Other	9	0.32
Earned money	2	0.07	Multiple	11	0.39
Multiple	1	0.04	No info	1	0.04

Notes: The dataset comprises 26 papers, covering 28 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).

estimates, yielding an average of approximately five observations per paper (median: 4; 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 of donations by 50%, either by using a 1:1 matching or by offering a 50% rebate on donations. Eleven studies also used a 33% price reduction (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 63 observations using a matching treatment and 74 using a rebate treatment (22 of which use an explicit tax framing).

Descriptive statistics on elasticities are presented in Table B.3 in the Online Appendix. The sample mean of the total donation elasticity is -1.66 ($SD = 1.73$), with values ranging from -7.33 to 1.77. For checkbook donations, the elasticity is, on average, smaller, at -0.69 ($SD = 1.05$). Net donations have a mean elasticity of -0.20 ($SD = 0.93$). Total donation elasticity estimates are plotted in Figure 2. 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

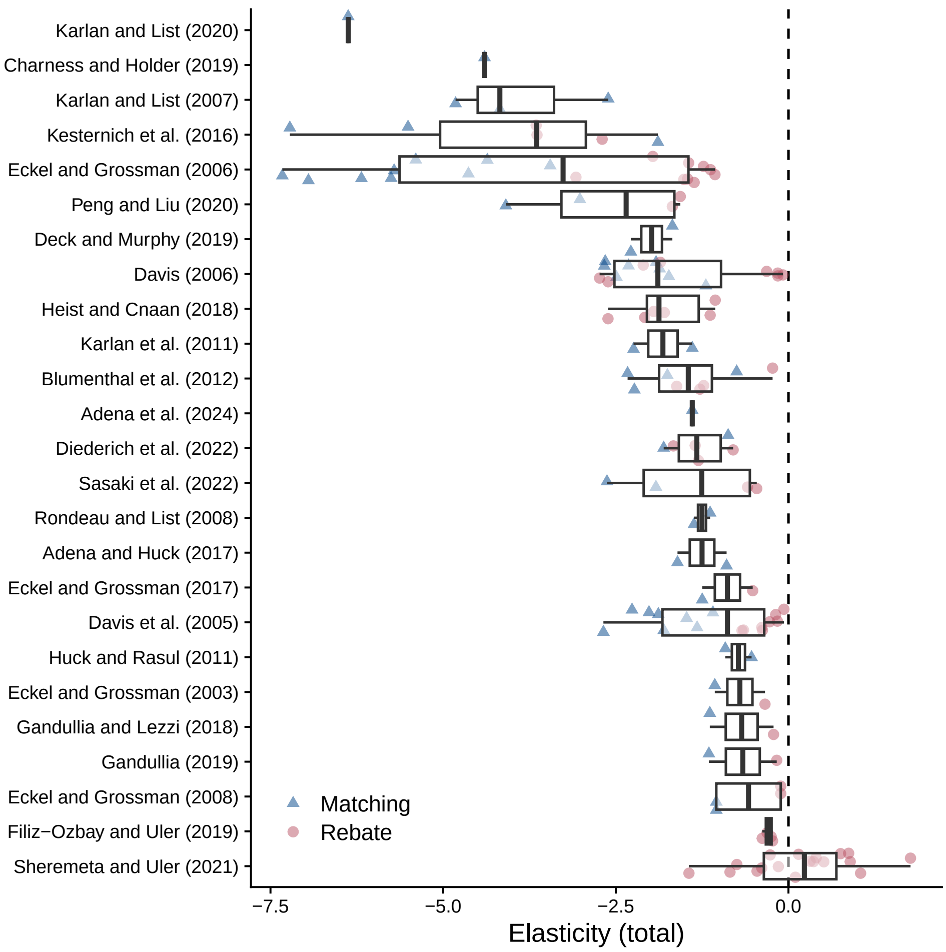

FIGURE 2: Distribution of total donation elasticities. *Notes*: Figures B.2 and B.3 in the Online Appendix show the distributions of checkbook donation elasticity and net donation elasticity, respectively.

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 (DerSimonian and Laird, 1986; Borenstein et al., 2009):

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

where $\varepsilon_i \sim \mathcal{N}(0, se_i^2)$ is a sampling variation of e_i as an estimate of $\bar{e}_i$, and the observation-specific "true" elasticity $\bar{e}_i$ is decomposed into e_0 (the overall mean) and a observation-specific random effect μ_i, which captures between-observation heterogeneity. It is further assumed that $\mu_i \sim \mathcal{N}(0, \tau^2)$, where τ^2 captures the variance of the true observation-specific elasticities beyond sampling error. 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 estimated via restricted maximum likelihood (REML), which is less biased than the DerSimonian and Laird method-of-moments estimator (Viechtbauer, 2005). Since our sample comprises a relatively small number of independent studies (clusters), conventional cluster-robust standard errors can be downward-biased, leading to over-rejection of null hypotheses. To address this, we report inference based on the bias-reduced linearization (CR2) cluster-robust variance estimator with Satterthwaite degrees of freedom (Tipton, 2015; Pustejovsky and Tipton, 2018), which provides more reliable finite-sample inference when the number of clusters is small.

Note that our dataset includes *statistically dependent* estimates of $\bar{e}_i$, 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 a three-level random-effects meta-analysis to account for the statistical dependence among multiple estimates reported within the same paper (Van den Noortgate et al., 2013). Let e_{pi} denote the ith estimate of e from paper p. The first level is $e_{pi} = \bar{e}_{pi} + \varepsilon_{pi}$, where $\bar{e}_{pi}$ is the observation-specific true price elasticity and $\varepsilon_{pi} \sim \mathcal{N}(0, se_{pi}^2)$ represents sampling error for the ith estimate in paper p. The second level is $\bar{e}_{pi} = \bar{e}_p + \mu_{pi}^{(2)}$, where $\bar{e}_p$ is the latent paper-specific mean elasticity and $\mu_{pi}^{(2)} \sim \mathcal{N}(0, \tau_{(2)}^2)$, with $\tau_{(2)}^2$ representing the within-paper variance in true elasticities. Finally, the third level is $\bar{e}_p = e_0 + \mu_p^{(3)}$, where e_0 is the overall mean elasticity and $\mu_p^{(3)} \sim \mathcal{N}(0, \tau_{(3)}^2)$, with $\tau_{(3)}^2$ representing the between-paper variance. Combining these levels yields

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

We estimate a random-effects model (2) and a multilevel 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.4 and B.5 for checkbook giving and net giving in the Online Appendix.

We find that the meta-analytical average elasticity is -1.601 for total donation, with a 95% confidence interval of $[-2.429, -0.772]$. 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 -0.567 (95% CI $[-1.005, -0.128]$), while for net donation, the parameter is -0.060 (95% CI $[-0.392, 0.272]$).

We also examine the I^2 statistic (Higgins and Thompson, 2002), which quantifies the proportion of total variance attributable to between-study heterogeneity. Formally, the I^2 statistic

Table 3: Meta-analytic average elasticity.

	Random-effects			Multilevel		
	(1) Total	(2) Checkbook	(3) Net	(4) Total	(5) Checkbook	(6) Net
$\widehat{e}_0$	-1.601^{***}	-0.567^{*}	-0.060	-1.745^{***}	-0.497^{***}	-0.088
$SE(\widehat{e}_0)$	(0.379)	(0.202)	(0.151)	(0.283)	(0.132)	(0.109)
95% CI	[−2.429, −0.772]	[−1.005, −0.128]	[−0.392, 0.272]	[−2.332, −1.158]	[−0.770, −0.225]	[−0.316, 0.139]
95% PI	[−4.626, 1.425]	[−2.030, 0.896]	[−1.256, 1.136]	[−4.267, 0.777]	[−1.683, 0.689]	[−0.878, 0.701]
τ^2	2.318	0.541	0.359			
I^2	99.391	97.375	94.105			
$\tau^2_{(2)}$				0.866	0.134	0.223
$\tau^2_{(3)}$				1.575	0.349	0.151
I^2_{within}				35.276	26.871	56.303
I^2_{between}				64.146	70.194	38.013
Num. clusters	24	25	21	24	25	21
Num. observations	131	128	108	131	128	108

Notes: (1-3) Benchmark random-effects model (equation (2)). (4-6) Multilevel model (equation (3)). Standard errors are clustered at the paper level with Satterthwaite degrees of freedom to account for the small number of clusters. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.005$.

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 multilevel model yields an average elasticity of −1.745 (95% CI [−2.332, −1.158]), which is slightly larger than that of the random-effects model. The heterogeneity measure I^2 adapted to the multilevel specification indicates that 64% of the total variance is due to between-paper heterogeneity, 35% is due to within-paper heterogeneity, and the remainder (< 1%) is due to sampling variation.

The 95% prediction intervals, which indicate the range within which the elasticity of a new study would be expected to fall, are wide.[3] For total donations, the prediction interval is [−4.267, 0.777], implying that while the average effect is clearly negative, a future study could plausibly find a small positive elasticity. Similar conclusions hold for checkbook donations, for which the prediction interval is [−1.683, 0.689], and for net donations, with a prediction

[3] The 95% prediction interval estimates the range within which the true effect of a new study would be expected to fall. For the random-effects model (2), it is given by $\widehat{e}_0 \pm t_{1-\alpha/2,k-2}\sqrt{\hat{\tau}^2 + SE^2(\widehat{e}_0)}$, where k is the number of studies. For the multilevel model (3), the prediction interval for a new study is $\widehat{e}_0 \pm z_{1-\alpha/2}\sqrt{\hat{\tau}^2_{(3)} + SE^2(\widehat{e}_0)}$, where $\hat{\tau}^2_{(3)}$ is the between-study variance component. This reflects the variability across studies rather than across observations within a study.

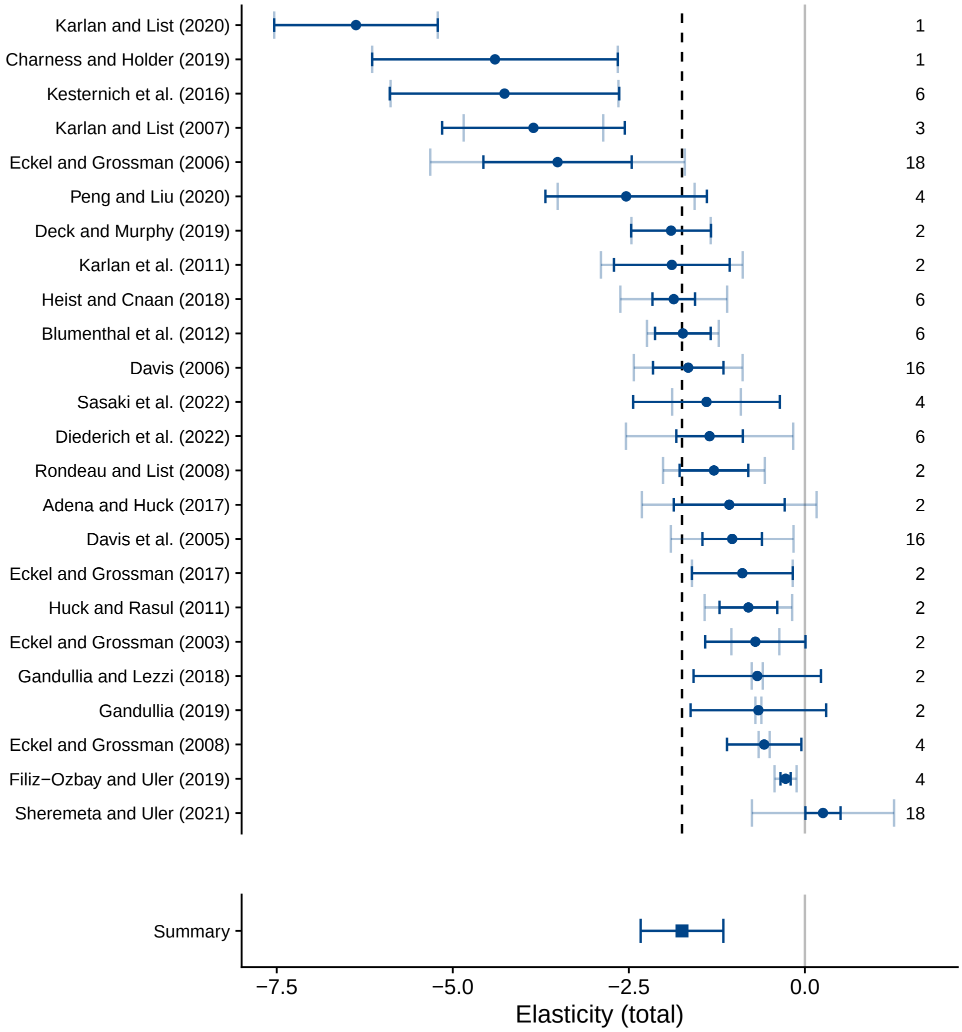

FIGURE 3: Forest plot of paper-level elasticity estimates (total giving). *Notes*: In the top panel, each dot represents the pooled estimate from a study (using a random-effects model), with the dark horizontal lines indicating the corresponding 95% CIs. Light horizontal lines show 95% CIs constructed using the median standard error within each study (Fernández-Castilla et al., 2020; Popova et al., 2026). Numbers on the right denote the number of elasticities in each study. The bottom panel shows the average elasticity (and 95% CI) estimated using a multilevel model.

interval of $[-0.878, 0.701]$.

As a minimal-assumption benchmark, we also compute unweighted study-level averages, assigning equal weight to each study regardless of precision. For each study, we first average the elasticity estimates within the study and then take the unweighted mean across studies. The unweighted mean elasticity of total donations is -1.855 (95% bootstrap CI $[-2.512, -1.313]$), compared with -1.745 from the multilevel model. For checkbook donations, the unweighted average is -0.538 (95% bootstrap CI $[-0.815, -0.291]$), and for net donations -0.169 (95% bootstrap CI $[-0.416, 0.050]$). These estimates are close to their model-based counterparts, indicating that the results are not sensitive to the precision-weighting structure.

The meta-analytic average elasticities are also robust to several sensitivity checks, reported in Online Appendix C. Reversing the priority order of the elasticity imputation hi-

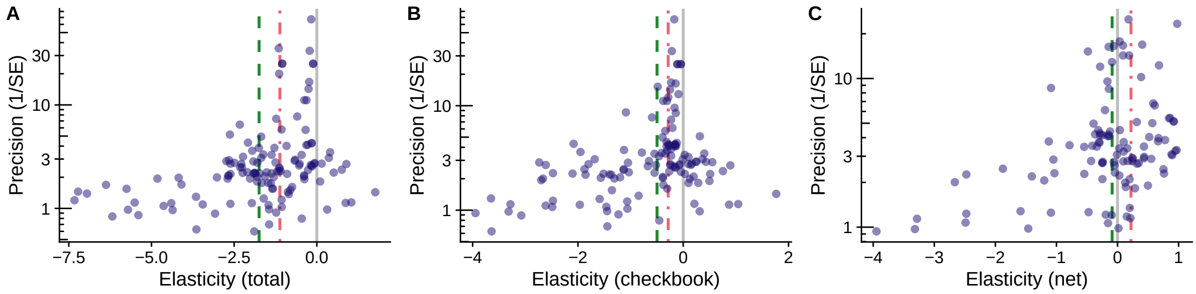

FIGURE 4: Relationship between reported/calculated elasticities and their corresponding precision ($1/SE$). *Notes*: The y-axis is shown on a log scale to improve visual clarity. The vertical green dashed lines represent multilevel estimates reported in columns (4)-(6) in Table 3. The vertical red dot-dashed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

erarchy (Section C.1), winsorizing the elasticities at the 5th and 95th percentiles (Section C.2), and dropping each study in turn (Section C.3) all leave the point estimates and significance patterns essentially unchanged.

4.2 Publication Bias

A common concern in any meta-analytic synthesis is that the published evidence may not represent the full universe of studies conducted due to selective reporting or publication bias. 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 to 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 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

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

	(1) Total	(2) Checkbook	(3) Net
Bias-adjusted estimate ($\bar{e}_{\text{lim}}$)	-1.116^{***}	-0.286^{***}	0.220^{*}
$SE(\bar{e}_{\text{lim}})$	(0.184)	(0.096)	(0.086)
95% CI	[−1.478, −0.755]	[−0.475, −0.097]	[0.051, 0.389]
Publication bias (α)	-5.212^{***}	-2.677^{***}	-3.151^{***}
$SE(\alpha)$	(1.273)	(0.574)	(0.606)
Num. observations	131	128	108

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

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.[4]

Results, presented in Table 4, indicate that there is evidence of publication bias. The parameter α is statistically significant and negative ($p < 0.005$ for all three outcomes), indicating that studies with a stronger price elasticity (i.e., larger in absolute terms) are often those with lower precision (i.e., larger variance of the estimator). Correcting for publication bias pushes the meta-analytic elasticities upward. For total and checkbook donations, the bias-adjusted estimates remain negative and statistically significant (−1.116 and −0.286, respectively), confirming that the qualitative conclusion of price-responsive giving survives the correction. For net donations, however, the bias-adjusted estimate turns positive (0.220), suggesting that the near-zero unadjusted estimate may itself partly reflect selective reporting.

Another concern for meta-analyses is p-hacking, or the tendency to selectively report

[4]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).

specifications based on the statistical significance of their results. Stefan and Schönbrodt (2023), for example, identify the selective inclusion of control variables as one method used to reduce p-values. A recent approach to detecting and correcting for such selective reporting is the Meta-Analysis Instrumental Variable Estimator (MAIVE; Irsova et al., 2025), which instruments standard errors that may be affected by specification selection with sample size, thereby making the estimator less susceptible to manipulation.

The first-stage results, reported in Table B.7 in the Online Appendix, show that sample size is not significantly associated with the standard errors of the reported elasticities (maximum F-statistic below 3). This weak first stage likely reflects that elasticity standard errors in our sample depend heavily on factors other than sample size, including the magnitude of the price change, baseline donation levels, and the method used to construct the elasticity (reported, imputed from treatment effects, or computed from group means). Without a relevant instrument, MAIVE cannot reliably correct for selective reporting.[5] It is therefore difficult to assess and correct p-hacking in our data using existing methods.

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 and (2) 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 first result is that there is no statistically significant difference between the estimated price elasticities of checkbook donations in the matching and rebate conditions ($p > 0.20$). The point estimate for checkbook giving is in the predicted direction: the elasticity is less negative under matching than under rebate. However, this difference is not statistically significant. Second, contrary to the predicted equivalence for net and total giving, the elasticities of net and total giving are larger in absolute value under matching than under rebate; the difference is statistically significant for both total and net donations ($p < 0.005$). These results align with the experimental results of Eckel and Grossman (2003).

This pattern helps clarify the source of the matching advantage. Checkbook responsiveness does not differ significantly between matching and rebate, although the positive matching coefficient is in the predicted direction. Given similar checkbook responses, matching mechanically generates a larger total-donation elasticity because the charity receives both

[5] An alternative method for investigating p-hacking, the Right-Truncated Meta-Analysis (RTMA; Mathur, 2024), is also not well suited to our setting. RTMA assumes that p-hacking consistently favors statistical significance in a specific direction, but for price elasticities, the relevant selection margin is ambiguous: publication decisions may depend on the significance of the elasticity itself, the matching-rebate comparison, or other study features. In addition, RTMA estimates the underlying effect-size distribution only from nonaffirmative (statistically insignificant) estimates, and our relatively small sample yields too few such estimates to support reliable inference.

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

	(1) Total	(2) Checkbook	(3) Net
Matching	-1.495^{***}	0.301	-0.822^{***}
	(0.343)	(0.210)	(0.156)
Constant	-0.902^{***}	-0.659^{***}	0.427^{***}
	(0.258)	(0.166)	(0.091)
Num. clusters	24	25	21
Num. observations	131	128	108

Notes: The dependent variables are: (1) Total elasticity (received by charities); (2) Checkbook giving elasticity (given by subjects); (3) Net elasticity (actually paid by subjects). Standard errors are clustered at the paper level with Satterthwaite degrees of freedom to account for the small number of clusters. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.005$.

the donor's contribution and the matching grant. The net-giving result follows analogously, since net giving equals checkbook giving under matching but is reduced by the refund under rebates.

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.4 and B.5 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 -2.440 (95% CI $[-3.215, -1.665]$) under matching, but only -0.728 (95% CI $[-1.163, -0.294]$) under rebates.

In Table 6, we present heterogeneity analysis with more moderators (price variation, location, type of experiment, and type of incentive). Adding these 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.

Regarding the moderating effects of the covariates on the price elasticity of donations, we find that, except for the matching dummy, no other covariate is statistically significant. In particular, studies conducted outside the United States do not report statistically significant differences in elasticities. Prior meta-analyses in related domains often find that treatment effects are larger in laboratory than in field settings (Matousek et al., 2022; Cala et al., forthcoming). In our data, however, the experiment-type indicator itself does not significantly predict the overall level of price elasticities ($p > 0.1$).

To examine whether 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 setting difference appears in the rebate–matching comparison: when the matching indicator is interacted with

Table 6: Meta-regression analysis.

	(1) Total	(2) Checkbook	(3) Net
Matching	-1.034^{***}	0.105	-0.653^{**}
	(0.061)	(0.060)	(0.140)
d_p	1.270	0.578	0.393
	(1.150)	(0.371)	(0.286)
Location: Non-USA	−0.662	−0.295	−0.289
	(0.284)	(0.133)	(0.197)
Experiment: Field/Online	0.404	0.163	0.456
	(0.324)	(0.092)	(0.224)
Incentive: Own money	−0.245	−0.101	−0.161
	(0.332)	(0.105)	(0.224)
Incentive: Other	0.571	0.482	−0.306
	(0.721)	(0.294)	(0.181)
Constant	0.052	−0.068	0.476^{*}
	(0.530)	(0.197)	(0.164)
Num. clusters	24	25	21
Num. observations	131	128	108

Notes: The dependent variables are: (1) Total elasticity (received by the charity); (2) Checkbook giving elasticity (given by subjects); (3) Net elasticity (actually paid by subjects). Standard errors are clustered at the paper level with Satterthwaite degrees of freedom to account for the small number of clusters. *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.005$.

the field/online indicator, the rebate–matching difference in total-donation elasticities is attenuated outside the laboratory, although it remains negative. This pattern is in line with the broader meta-analytic evidence that laboratory settings tend to produce larger treatment effects, but in our context it appears as a moderation of the rebate–matching gap rather than as a general shift in the level of price elasticities.

The robustness of these meta-regression results to model specification uncertainty is confirmed by a model-averaging exercise over all $2^6 = 64$ moderator subsets (Online Appendix C.4).

5 Conclusion

In this paper, we conduct a quantitative meta-analysis of the price elasticity of charitable giving. Drawing on 137 point estimates from 26 primary studies, we estimate a meta-analytic mean price elasticity of total donations of −1.75. Although we detect evidence of publication bias, adjusting for this bias does not materially change our conclusions.

Our primary contribution to the literature is to compare 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 −2.44 versus −0.73. The matching elasticity is about 3.3 times as large as the rebate elasticity, which is close to the threefold ratio reported by Eckel and Grossman (2003). This suggests that the original matching advantage persists when the broader experimental evidence is synthesized.

Beyond establishing the average 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, although it remains persistent. This finding is consistent with previous meta-analyses in the social sciences, which show that participants in laboratory experiments tend to respond more strongly to experimental treatments, leading to larger estimated treatment effects (in absolute value) than those observed in field settings (Matousek et al., 2022; Cala et al., forthcoming). At least two mechanisms may explain this pattern in our context. First, laboratory experiments typically ensure that participants carefully read the instructions, complete comprehension checks, and face few distractions, whereas participants in field experiments often devote less attention to the intervention. As a result, differences between matching and rebate incentives may be more salient in the laboratory. Second, many field experiments are conducted with previous donors, who are likely to be more familiar with charitable giving mechanisms. These experienced donors may be more likely to recognize that matching grants and rebates imply similar effective prices of giving and therefore respond more similarly to the two types of incentives. Matching schemes nevertheless 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 acknowledgment. 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, computable price-reduction parameter (d_p), even when alternative measures of price elasticity are available, so we can 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 price changes. 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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