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Are Tax Incentives for Charitable Giving Efficient? Evidence from France†

By GABRIELLE FACK AND CAMILLE LANDAIS*

This paper estimates the effect of tax incentives for charitable contributions in France. We focus on two reforms that increased the nonrefundable tax credit rate for charitable contributions by 32 percent. We use a difference-in-difference identification, comparing the evolution of contributions for groups of households with similar income, but different taxable status due to differences in family size. We control for censoring issues and investigate distributional effects using a three-step censored quantile regression estimator. We find that the price elasticity of contributions is relatively small, but tends to increase with the level of gifts. (*JEL* D14, D64, H24)

In many countries, charitable contributions benefit from a favorable tax treatment that may take the form of a deduction from taxable income or of a tax credit. Recently, these tax incentives have been further promoted by the governments of several European countries, as a way to increase private funding for fields like education, research and culture. Assessing the efficiency of these tax treatments is therefore of critical interest for public policy. Compared to charitable giving in the United States, the level of private gifts in France has thus far been relatively low; expressed as a percentage of gross domestic product (GDP), charitable contributions reported in tax files in France in 2001 were less than one-tenth of those reported by US taxpayers.[1] The weakness of private charitable contributions in France has served as an impetus for several reforms over the last 15 years that aimed to increase tax incentives for giving to charities. The French system, which consists of a nonrefundable

* Fack: Universitat Pompeu Fabra and Barcelona GSE, Universitat Pompeu Fabra, Department of Economics and Business, Jaume I Building, Ramon Trias Fargas, 25-27, 08005 Barcelona, Spain (e-mail: gabrielle.fack@upf.edu); Landais: University of California, Berkeley, #508-1 Evans Hall #3880, Berkeley, CA 94720-3880 (e-mail: camille_landais@berkeley.edu). This work was financially supported by the CEPREMAP and would not have been possible without the support of the Ministry of Finance. We are particularly grateful to Fabrice Pesin, Sandrine Duchêne, and Cedric Audenis, who offered us the opportunity to perform an internship at the Direction Générale du Trésor et des Politiques Economiques to work on this subject, and Jacques Malet and Sophie Rieunier for sharing exclusive surveys on charitable giving behaviors with us. We would also like to thank Thomas Piketty, Tony Atkinson, Esther Duflo, Marc Gurgand, Eric Maurin, Bernard Salanie, Dan Silverman, Wojciech Kopzuck, Pierre-Yves Cabannes, Julien Grenet, Laurent Bach, an anonymous referee as well as participants of the CREST Microeconometrics and the IFS seminars, of the SOLE and TAPES conferences of the Congress of the International Institute for Public Finance, and of the Applied Lunch Seminar at Universitat Pompeu Fabra for helpful comments and suggestions.

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[1] In 2001, gifts reported by US taxpayers amounted to 2.2 percent of total adjusted gross income and 1.4 percent of US GDP, whereas gifts reported by French taxpayers represented 0.21 percent of total gross income and 0.08 percent of French GDP.

tax credit equal to 66 percent of the gift, stands out as a very generous scheme. The French tax credit rate is currently the highest rate among countries with tax credits for charitable giving,[2] but it is also higher than the top marginal tax rate in most countries. This implies that French subsidies for charitable giving are much more generous than, for instance, the US incentive system, which works as a deduction from taxable income. Variations in the French tax credit rate due to tax reforms can be exploited as natural experiments in order to estimate the efficiency of tax incentives toward charitable contributions.

Several empirical papers have used US data to study the effect of tax incentives for charitable giving, focusing on the estimation of the price elasticity of charitable contributions. Early studies (such as Martin S. Feldstein and Amy Taylor 1976) use cross-sectional data to estimate both price and income elasticities of charitable giving. They find that the elasticity of giving with respect to the tax-defined price was greater than one in absolute value, suggesting a high responsiveness to tax incentives. However, these early studies were plagued by identification problems caused by the simultaneous variations of income and price of giving. Since the deduction rate is equal to the marginal tax rate in the United States, and is therefore a function of income, it is difficult to disentangle the effect of a change in income from the effect of a change in price. Studies on panel data (including William C. Randolph 1995; Kevin Stanton Barrett, Anya M. McGuirk, and Richard Steinberg 1997; and Jon Bakija 2000) have tried several methods to separately estimate the transitory changes in prices caused by fluctuations in income and the permanent changes in prices (for a review of studies that use US data, see Bakija and Bradley Heim 2008). When decomposing income and prices in transitory and permanent components, Randolph (1995) finds estimates of the elasticity of giving with respect to the permanent price of giving ranging from -0.3 to -0.5, which is much lower than earlier findings. However, Gerald E. Auten, Holger Sieg, and Charles T. Clotfelter (2002), relying on a different method to identify transitory and permanent income shocks,[3] find higher permanent price elasticities ranging from -0.79 to -1.26, and lower transitory elasticities than other studies. Overall, the empirical estimations of the elasticity of charitable giving have, so far, produced mixed results. Moreover, the debate regarding the estimation of the effect of incentives toward charitable giving has generally focused on the way to disentangle transitory and permanent changes in price and income, while other issues have largely been neglected in such investigations. Recent papers have pointed out two additional concerns regarding the previous estimations. First, Ralph Bradley, Steven Holden, and Robert McClelland (2005) show that censoring may severely affect the estimation of the elasticity of charitable giving in samples where a significant portion of households do not contribute. They estimate the elasticity of charitable giving on a cross-section of US taxpayers, both with the parametric methods classically used to deal with censoring (such as Tobit or Heckman) and with semi-parametric methods. Their results suggest that the parametric assumptions on which the classical methods rely do not hold, and they

[2] See (David Roodman and Scott Standley, 2006) for a comparison of tax incentives in various countries.

[3] They work directly on the variance-covariance matrix of income and prices and assume that these variables experience both random persistent shocks and transitory shocks, which disappear after one year.

find much lower estimates with semi-parametric methods than with a Tobit model. Second, Bakija and Heim (2008) show evidence of heterogeneity in the response to tax incentives. Using a long panel of US taxpayers with disproportionately high income, they estimate the elasticity of charitable giving to persistent price separately for different income groups and find that the response tends to be larger for wealthy households than for less wealthy households. Income is one of many possible sources of heterogeneity in households' response to the price of giving. Charitable giving may indeed be motivated by different motives, and the other sources of heterogeneity have been studied very little. In particular, empirical studies generally focus on the estimation of mean effects, but very generous donors' response to tax incentives might be very different from that of smaller donors.

Laboratory and in-the-field experiments have also been conducted to study the behavioral response of individuals to either monetary or nonmonetary incentives.[4] Karlan and List (2007) estimate a price elasticity of giving from a field experiment where different rates of matching subsidies were offered to random samples of individuals that had previously contributed to a nonprofit organization. They find that although matching subsidies have a significant effect on donations, large matching subsidies do not have a larger impact than smaller matches (which offer to match each dollar given with one additional dollar). The implied elasticity over the sample is -0.3, but this estimate cannot be compared directly to nonexperimental studies since it focuses on a one-time subsidy to one specific organization, and does not measure longer term effects on the individuals' charitable behavior.

In this paper, we rely on a natural experiment framework to identify the effect of exogenous variations in the price of giving. We use a quantile regression estimator to deal with censoring and investigate the heterogeneity of responses among households. More precisely, we study the response of French households to two tax reforms that took place in 2003 and 2005 and increased the tax credit rate for charitable contributions in France from 50 percent to 66 percent. These reforms create a pseudo-natural experiment framework, since taxable households experienced a 32 percent decrease in their price of giving during the period, whereas the incentives to give were not modified for nontaxable households, which did not benefit from any price reduction. We take advantage of the fact that the taxable status of households in France is determined not only by income, but also by the size of the family, and select treatment and control groups of taxable and nontaxable households with similar income from a large pseudo-panel of households. This strategy allows us to estimate the effect of tax incentives on charitable giving, while controlling for income effects and for unobserved shocks that could affect the income groups during the period. We use the three-step censored quantile regression estimator proposed by Victor Chernozhukov and Han Hong (2002) to address the problem of censoring in an easily computable way. The quantile regression estimator also allows us to investigate the heterogeneity of responses among the distribution of gifts.

[4] Analyses of monetary incentives, such as price subsidy or matching, include Dean Karlan and John A. List (2007), Catherine C. Eckel and Philip J. Grossman (2003), Stephan Meier (2007), and Steffen Huck and Imran Rasul (2007). Empirical studies of nonmonetary incentives include experiments on signals given by lead donations (List and David Lucking-Reiley 2002), reciprocity (Armin Falk 2007) or pro-social motivations (Bruno S. Frey and Meier 2004).

Our results show that the overall effect of the reforms is small. The estimated price elasticity of gifts is around -0.2 to -0.6 across quantiles, and below the level that would make the actual French tax credit rate optimal, unless there is significant crowding out between private and public funds. From a public policy perspective, the increase in charitable giving caused by the increase in tax incentives was actually smaller than the foregone revenue for the government. We also find evidence that the elasticity of gifts to the tax credit rate is heterogenous among taxpayers, suggesting that more generous donors react more to tax incentives than smaller donors. The heterogenous responses show that quantile regressions seem to be a more appropriate tool for studying charitable giving behavior than traditional models (such as Tobit), which rely heavily on the assumption that errors are homoscedastic.

The paper is organized as follows. In the next section, we present the theoretical framework for analyzing the efficiency of tax incentives toward charitable contributions. Section II describes the French tax treatment of charitable contributions and presents the data. The estimation strategy is explained in Section III. Results and sensitivity analysis are presented in Section IV.

I. Evaluating Tax Incentives

The theoretical justifications and the optimal design of subsidies to charitable contributions vary with the modeling of philanthropy. Models of charitable giving usually assume that individuals are not purely altruistic, but that they also enjoy a certain "warm glow" of giving. In other words, a person benefits not only from the total amount of public goods, but also from satisfaction obtained through her own contribution. If individuals were purely altruistic, there would be perfect crowding out between charitable contributions and government spending. However, with the warm-glow motive, the crowding out is not perfect and tax incentives might be justified.[5] Emmanuel Saez (2004) and Peter Diamond (2006) have investigated the optimal tax treatment of charitable contributions with warm glow of giving motives.

Here we adopt the theoretical framework developed by Saez (2004) to evaluate the efficiency of tax incentives, which expresses the optimal tax subsidies in terms of empirically estimable parameters. Saez considers a model where an individual's utility is a function of private consumption c, earnings z (which enter negatively in the utility to reflect the fact that labor supply is costly), their own charitable contributions g (the warm-glow motive), and the aggregate level of charitable contributions G. Individuals therefore maximize

$$\max U(c, g, z, G)$$

$$\text{s.t. } c + g(1 - t) \leq z(1 - \tau) + R,$$

[5] For a discussion of the models that assume a "warm glow" effect, see James Andreoni (2006).

where t is the subsidy rate and τ is the tax rate on earnings that is used to finance a lump-sum transfer R to all individuals and the subsidy on g. The number of individuals is large enough so that individuals view G as fixed when maximizing their utility.

Crowding-out effects are introduced into the model by allowing the government to directly contribute to the same public good by an amount G_0. The total amount of public goods becomes $G = G^P + G_0$, and G^P (the total of private contributions) is therefore directly affected by G_0, since G is a component of the Marshallian demand function of every individual $g^i(1 - \tau, 1 - t, R, G)$. The crowding-out effect can be expressed as a function of the average private contribution for the given tax parameters and a given G_0, denoted $\overline{G} = \overline{G}(1 - \tau, 1 - t, R, G_0)$. The crowding-out effect of increasing G_0 is $\partial \overline{G} / \partial G_0$, which we denote $\overline{G}_{G_0}$, and is usually assumed to be between -1 (complete crowding out) and 0.

In order to derive quantitative tax policy recommendations, Saez (2004) shows that in this set-up, it is useful to make three important assumptions:

(i) that there are no income effects on earnings at the individual level;

(ii) that the level of the contributions and the subsidy rate on charitable contributions do not affect earnings; and

(iii) that the compensated supply of contributions does not depend on the tax rate on earnings (in other words, that contributions are affected by a change in the tax rate on earnings only to the extent that it affects disposable earnings).

The latter two assumptions are implicitly made in the empirical literature on charitable contributions and Saez's (2004) model can be used to relate the findings of the empirical literature to a more general theoretical framework. Under these assumptions, the rule for assessing the optimality of the optimal subsidy rate t can be expressed as a function of ϵ_{1-t}, the elasticity of charitable contribution to its price $(1 - t)$:[6]

$$\epsilon_{1-t} = -\left(1 + \overline{G}_{G_0}\right). \tag{1}$$

In the preceding equation, it appears that in the absence of crowding out between charitable contributions and government spending ($\overline{G}_{G_0} = 0$), subsidies to charitable contributions should be increased when the elasticity is above one in absolute value and decreased when the elasticity is below one in absolute value. Saez (2004) notes that if the elasticity is treated as a constant parameter, as is typical in empirical studies, the formula does not provide an explicit expression for the optimal subsidy.[7] The formula nevertheless offers a simple rule for assessing whether the level of the subsidy is too high or too low given the estimated elasticity.

[6] In his model, Saez (2004) also introduces a social weight to reflect the distributive tastes of the government, but for simplicity we ignore this additional objective.

[7] If the elasticity is constant, and there is no crowding out, the optimal tax rate is either -1 or infinity.

It is also clear from this framework that the "golden rule" of an elasticity greater than 1 (in absolute value) to assess the efficiency of a subsidy toward charitable giving only applies under specific assumptions. If there is some crowding out ($\overline{G}_{G_0} \leq 0$), a subsidy might be efficient even if the elasticity of charitable giving is lower than one in absolute value. The intuition for this is that if there are some important crowding out effects, it is better to rely more on private contributions so that the subsidy rate must be increased to higher levels, even if private contributions respond a little less to these higher subsidies. Moreover, this rule assumes that the government is not constrained in its level of contributions to the public good and can adjust it in response to changes in the level of private contributions, but this might not always be the case (for example, poor relief expenditures might be limited by political economy considerations). Furthermore, subsidies toward charitable giving might also be justified at lower elasticity levels if private funds are used much more efficiently than public funds.

This optimality condition can be reconciled with a simple public finance objective if we assume that financing the subsidy by the tax rate τ has only second-order effects on charitable behaviors and earnings (that is, we neglect all income effects of the tax credit rate t). In this partial equilibrium framework, where the government only wants to promote charitable contributions, increasing the subsidy rate will be efficient from a public finance point of view if the total increase in charitable contributions is greater than the loss in tax revenues, or in other words, if it yields a positive increase in money actually given by taxpayers, net of the subsidy. At the optimum, this condition can be summarized as $\Delta\left[(1-t^*)G\right] = 0$.

Assuming that there is no crowding out and that changes in the subsidy rate do not affect earnings, for small changes of t, the public finance objective leads to the same efficiency rule (1) as in Saez's (2004) framework (if crowding out is excluded). Hence, if we want to assess the efficiency of the reform not according to a first-best criterion, but according to a simple public finance objective, excluding crowding-out effects, specific redistributive tastes of the government, and distortionary costs to collect taxes, we are led to the same simple rule for policy recommendations, that subsidy should be increased if the elasticity is greater than one (in absolute value) and should be decreased if it is less than one (in absolute value).

II. The French Tax System and Charitable Contributions

A. *French Tax Incentives Toward Philanthropy*

The French System.—A tax incentive toward charitable giving has existed in France since 1954, but has been significantly modified over time. The initial deduction mechanism, which worked as a deduction from taxable income, was replaced in 1989 by a nonrefundable tax credit of 40 percent. With a nonrefundable tax credit, all taxpayers benefit from the same tax credit rate equal to t percent of the gift,[8] regardless of income level. This differs from the US and UK systems of deduction

[8] The gift can be deducted up to a ceiling currently equal to 20 percent of taxable income. Moreover, since 2003, if the gift exceeds the ceiling, its reporting can be spread out over five years.

from taxable income, where the deduction rate is equal to the marginal tax rate faced by the individual, and therefore increases with income. The additional feature of the French system is that the tax credit is nonrefundable, implying that the deduction cannot exceed the income tax that is due for taxable households. Nontaxable households do not benefit from the tax incentive either.

Since the late 1980s, the French government has used various strategies in an attempt to boost private philanthropy. After simplifying the law applicable to private foundations of public interest, they turned to tax incentives, implementing three main reforms that exogenously changed incentives toward charitable contributions. The tax credit rate was raised three times:[9] from 40 to 50 percent in 1996,[10] from 50 to 60 percent in 2003,[11] and from 60 to 66 percent in 2005.[12] We take advantage of the variations in the tax credit rate brought about by the 2003 and 2005 reforms to estimate price elasticities of charitable contributions.

The Timing of Tax Reforms.—To understand the timing of tax reforms in France, note that the French tax system does not function as a withholding tax. In year n, people fill out a tax form to declare income earned in year $n - 1$. Tax parameters applicable to current income can be changed by laws during the year. The full set of fiscal parameters are then known only at the end of the year, in late December, when the Fiscal Law is voted on, after all income has been earned and charitable contributions have been made.

For the 2003 reform, a law was passed in August in order to encourage private philanthropy and it was mentioned that the Fiscal Law for year 2004 (passed in December 2003, applicable to income earned in 2003) would increase the tax credit rate for charitable contributions. Therefore, taxpayers could have changed their charitable behaviors in the second half of 2003, in expectation of an increase of tax incentives, even though the new tax credit rate was fully operational only from 2004 onward. For this reason, we decided not to include year 2003 in our baseline estimation.[13] The second reform was passed in the beginning of 2005 as a part of a law on social cohesion. We assume that taxpayers were able to take into account the new rate in 2005.[14]

Ultimately, it seems that people are well aware of the existence of a tax credit scheme. Studies based on opinion polls report that the vast majority of households (around 85–90 percent in the general population[15]) are aware of the existence of the

[9] A specific rate was also created in 1989 to favor charities fighting against poverty. The rate applies to gifts smaller than a fixed threshold (470 euros in 2005) and was modified at the same time as the rate applicable to standard gifts: from 50 percent to 60 percent in 2003 and from 60 percent to 75 percent in 2005. Given that this rate applies only to specific gifts, and that the change in the rate mirrored the change in the main credit rate, we use the latter in our analysis.

[10] *LOI 96-559 du 24 juin 1996 portant diverses mesures en faveur des associations.*

[11] *LOI 2003-709 du 1er août 2003 relative au mécénat, aux associations et aux fondations.*

[12] *LOI 2005-32 du 18 janvier 2005 de programmation pour la cohésion sociale.*

[13] However, we verify that removing (or not removing) year 2003 from our sample does not significantly change our estimates.

[14] We also checked that results are similar if we assume that individuals are not fully aware of the reform until the next fiscal year 2006.

[15] See the report *La Générosité des Français*, Centre d'Étude et de Recherche sur la Philanthropie (CerPhi), editions 2006, http://www.cerphi.org/.

TABLE 1—DESCRIPTIVE STATISTICS: ESTIMATION SAMPLE

Year	Percentage of donors	Mean gift among donors	Mean disposable income	Mean *Quotient Familial* per household	Observations
1998	12	125	17,922	1.85	53,904
1999	12	128	18,127	1.84	57,856
2000	12	127	18,361	1.82	45,882
2001	12	133	18,649	1.82	44,435
2002	12	144	18,695	1.80	56,774
2003	12	141	18,530	1.79	53,904
2004	13	133	18,559	1.78	48,012
2005	13	153	18,730	1.78	45,710
2006	12	179	19,036	1.77	48,308

Notes: Authors' calculations from *Echantillons Lourds*. Contributions and income are expressed in 2004 euros. *Quotient Familial* is the number of units granted to the household to compute its tax liability following a family-splitting system. Each adult member stands for 1 unit, the first and second child for ½ each, and every child from the third child on stands for 1 additional unit.

nonrefundable tax credit for charitable contributions. Donors have ample opportunity to learn of changes in the tax law since information on the tax credit rate is usually sent by charities in mailings. A survey conducted by the CerPhi for the charity *Secours Catholique*[16] shows that 98 and 92 percent of taxable and nontaxable regular donors, respectively, are aware of the tax incentive scheme.

B. *Data*

Our data come from a unique sample of the French *Direction Générale des Impôts*, and include more than 500,000 taxpayers every year. This sample of tax files is called "*Echantillon lourd*" and is made up of repeated cross-sections of taxpayers drawn every year by the tax administration in order to forecast the evolution of tax revenues. The variables available in the dataset correspond to the information contained in income tax forms: detailed income level and composition, family size, age, matrimonial status, and expenses eligible for deductions or tax credits.

The main interest of this dataset lies in the fact that, because filing a tax form is compulsory in France, we have data for both taxable and nontaxable taxpayers. Households have incentives to fill out a tax form even if they are not taxable because the taxable income calculated by the tax administration on the basis of the tax declaration is used as a reference to determine eligibility for several means-tested benefits. We can therefore build up a large sample of roughly 50,000 households close to the taxation threshold for each year of our analysis. Table 1 presents the descriptive statistics of the households selected in our sample. Overall, only 12–13 percent of households report a gift, so the mean level of gifts in the sample is low. The mean level of gifts among donors is 125 euros for 1998. Additional data in the Appendix includes statistics at a more detailed level, and show that some groups of families with children have a much higher income than the sample mean and are still nontaxable.

[16] See the report *La Générosité des Français*, 12th edition, Jacques Malet, 2007.

Another advantage of using tax declarations is that reported gifts are likely to accurately reflect actual gifts because households are sent a receipt certified by the charity that they have to join to their tax file, in order to show that the amount declared to the tax authority matches the amount recorded by the charity. This reporting mechanism makes it almost costless for a household to report its contributions and explains why the vast majority of contributions to charities are reported in tax data.

Our estimation strategy relies on a difference-in-difference framework between households with the same taxable income, but with some being taxable and others being nontaxable because of the functioning of the French family-splitting. In our setting, a key assumption is that nontaxable households actually report part of their gifts in their tax declarations even though they do not benefit from the charitable tax credit. In fact, we do not need to assume that these households report all their contributions, but only part of their gifts, and that this fraction is constant over time.[17] Two types of evidence help us to assess the validity of this identifying assumption. First, we had access to an external survey, jointly conducted on a sample of 2,047 individuals in 2007 by the CerPhi and the research laboratory GREGOR of the *Institut d'Administration des Entreprises de Paris*, which investigates the reporting behavior of households. Among households whose monthly income is between 1,000 and 4,000 euros, and who declare that they give to charity, 81 percent of taxable households report their gifts (all the time or some of the time), compared with 46 percent of nontaxable households.[18] These raw figures are unadjusted for potential income effects and cannot be directly compared with tax data, as the information is self-reported by individuals and the sample is not a representative sample of the population. But they show that even if nontaxable households do not report their gifts as often as taxable households, a significant proportion still does so. This behavior may be explained by taxpayers' efforts to comply with the tax guidelines, which ask everyone to truthfully report the level of giving in their tax declaration, and because it is not costly to report a gift (since charities send a receipt to all contributors). Second, as we can see in Figure 1 and in Tables A1 and A2 in the Appendix, our tax data show that the fraction of households reporting gifts among *nontaxable* groups is substantial, and that the distribution of donations among *nontaxable* groups is commensurate to that of *taxable* groups. This suggests that, for a similar level of income, *nontaxable* groups do not significantly underreport their gifts compared to *taxable* groups in our sample. Unfortunately, there is no panel dataset that allows us to check whether the reporting behavior for nontaxable households evolves over time, but there is no reason to expect that it would have changed at the time of the reforms.

[17] We can consider two cases. If we assume that smaller donors are less likely to report their gifts than other donors, then underreporting will not affect the estimation of the defined conditional quantiles. If we assume that underreporting is spread across the distribution of gifts, then we must assume that unobservable shocks have a uniform effect on the distribution of gifts.

[18] The figures are also higher for regular donors. In the survey conducted by CerPhi for *Secours Catholique*, 95 percent of taxable donors always report their gifts in their tax declaration (unfortunately, the question was not asked of nontaxable households).

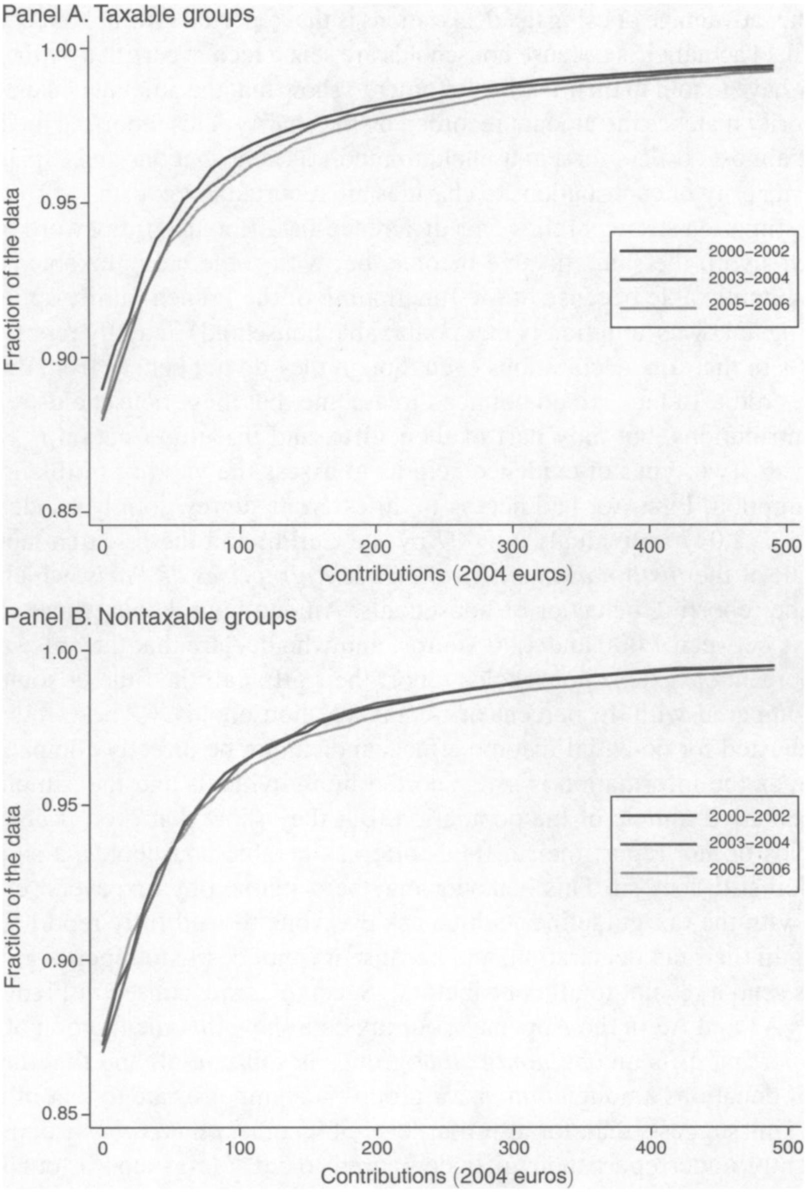

FIGURE 1. EVOLUTION OF THE CUMULATIVE DISTRIBUTION FUNCTION OF GIFTS (*Constant 2004 Euros*)

Notes: DGI, households with taxable income between the thirty-fourth percentile and the eighty-third percentile of the taxable income distribution, and with $QF >= 1$ and $QF <= 5$. "Taxable groups" denotes households belonging to groups just above the threshold where the contribution tax credit kicks in, namely people with $QF = 1$ and income between P33–P44, or with $QF = 1.5$ and income between P44–P54, or $QF = 2$ and income between P54–P62, or with $QF = 2.5$ and income between P62–P68, or with $QF = 3$ and income between P68–P76, or with $QF = 4$ and income between P76–P83. Conversely, "Nontaxable groups" denotes households belonging to groups just below the threshold. Data are pooled in three periods: for example "2000–2002" pools observations for years 2000 to 2002.

Source: Echantillons Lourds

III. Estimation Strategy

In this section, we describe our estimation strategy, which relies on the exogenous change in tax laws, in a difference-in-difference identification framework, and a three-step quantile regression estimator.

A. *Identification: Difference-in-Difference Strategy*

The tax credit rate varies over time only for taxable households. To identify the effect of credit rate variations in the presence of unobservable shocks contemporaneous with tax reforms, a proper counterfactual is needed for what would have happened to contributions in the absence of tax reforms. Nontaxable households are good candidates to serve as a control group since their price of giving is one and is not affected by nonrefundable tax credit rate variations. However, we cannot compare all taxable and nontaxable households because being taxable is largely determined by the income level of the household and the support of the covariates of our model varies substantially with income level. In order to design credible treatment and control groups, it is necessary to find variations in tax status that are orthogonal to income, stable over time, and unaffected by variations in the tax credit rate. Our strategy takes advantage of the existence of the mechanism of family tax-splitting in the French tax system, which creates discontinuities in the taxable status according to the number of persons in the household. We can therefore identify the effect of tax incentives toward charitable giving by comparing the evolution of gifts over time for households that have similar income, but are either just above or just below the taxable threshold due to differences in family size.

More specifically, the principle of this tax-splitting mechanism called "*Quotient Familial*" (thereafter *QF*) is as follows: each household is granted a *QF* number n, which increases with the size of the household. A single person is quantified as $n = 1$, a married couple $n = 2$, the first two children are equal to 0.5 each, and children beyond the second child are 1. Gross income tax is determined by applying the tax scheme to the ratio Y/n, where Y is taxable income.[19] In the following, we say that households are *taxable* if Y/n is greater than a minimum tax allowance, and *nontaxable* if Y/n is less than this threshold. For the former, tax credits kick in and actual tax liability is determined by further subtracting nonrefundable tax credits (such as credits for charitable giving) and then refundable tax credits from the calculated tax. In order to ensure that the price of charitable giving is not correlated with the level of contributions, we use the *taxable* status as defined above (without taking into account tax credits) to determine the price of giving faced by each household. In other words, we replace the actual price of gifts by the first-euro price.[20] The *taxable* status is thus solely a function of gross income and family size, and is independent of the level of charitable contributions.

[19] Taxable income is gross income minus some deductions.

[20] It is a standard procedure in the literature to use the first-dollar price as an instrument for the actual price of gifts (see for example, Bakija and Heim 2008). In our quantile regression, we directly use the first-euro price in a reduced form framework. We did not want to further complicate the estimation strategy, as the models proposed in the literature to deal with instrumental variables in the censored quantile regression framework are still quite new

As a result of the functioning of the QF, some households with the same level of income, but different family sizes, have different incentives. Our methodology is to compare, within stable income groups over time, households that are above the tax allowance threshold and households that are below the threshold due to one (or one-half) additional unit of QF. Households above the threshold experience variations in their tax incentives over time, whereas households below the threshold do not experience these variations. Both groups are assumed to be subject to the same unobservable shocks on contributions contemporaneous with tax reforms.

More precisely, our treatment and control groups are defined as follows. We first take households with income ranging between the thirty-third and forty-forth percentiles of the taxable income distribution (P33–P44), and with $QF = 1$ or $QF = 1.5$. Since the taxable threshold for households with $QF = 1$ is stable and roughly equal to the thirty-third percentile of the income distribution over time, and the threshold for households with $QF = 1.5$ is roughly equal to the forty-fourth percentile, households within the P33–P44 income group with $QF = 1$ are always taxable, whereas households with $QF = 1.5$ are not and can be used as a control group. We similarly compare within the P44–P54 income group households with $QF = 1.5$ (*taxable*) versus households with $QF = 2$ (*nontaxable*), within the P54–P62 income group households with $QF = 2$ (*taxable*) versus households with $QF = 2.5$ (*nontaxable*), within the P62–P68 income group households with $QF = 2.5$ (*taxable*) versus households with $QF = 3$ (*nontaxable*), within the P68–P76 income group households with $QF = 3$ (*taxable*) versus households with $QF = 4$ (*nontaxable*) and within the P76–P83 income group households with $QF = 4$ (*taxable*) versus households with $QF = 5$ (*nontaxable*). We end up with 12 income × QF groups. Six of these groups contain only *taxable* households, and 6 contain only *nontaxable* households. In order to get a larger sample size for inference, we pool together all the groups, under the assumption that the price elasticity is the same across income groups P33–P44, P44–P54, P54–P62, P62–P68, and P68–P76.

The specification is as follows:

$$\ln(gift_i) = \sum_j \alpha_j \times group_{ji} + \beta(\ln(1 - t_n) \times taxable_i) + \sum_n \gamma_n Year_{ni} + \sum_k \theta_k X_{ki} + \epsilon_i, \tag{2}$$

where $\ln(gift_i)$ is the logarithm of the gift plus 1 euro (the standard method used in the literature to take into account people who do not give), $group_j$ stands for the 12 indicator variables for the 12 income × QF groups, and $taxable_i$ is an indicator variable equal to 1 for households belonging to a *taxable* group. Identification of the price response of contributions in this difference-in-difference framework is brought by the coefficient β. To control for time effects affecting all groups, we include a set

and they usually impose strong restrictions on the distribution of errors (see Joshua D. Angrist and Jörn-Steffen Pischke 2009).

of year dummies. Controls X_i' include the log of disposable income,[21] age, marital status, and a dummy variable for being a wage earner. The error term is ϵ_i.

This strategy may raise three concerns. First, as discussed previously, one may question the accuracy of the donation figures for *nontaxable* households, because they have no incentives to report their gifts. We provide evidence in Table A1 showing that the fraction of households reporting gifts among *nontaxable* groups is substantial. In any case, our strategy does not require that nontaxable households report all their gifts, only that the fraction of donations that they report is stable over time.

The second question concerns the stability of the tax status over time. If households are highly mobile across groups, moving constantly across the taxable status threshold, this may affect our estimates in two different ways. On the one hand, the estimated price elasticity of gifts β in (2) may mix transitory and permanent price effects, because households that are taxable, but were not taxable the year before, may optimize the timing of their gifts to take advantage of the tax credit. On the other hand, the estimated effect of price β may underestimate the true elasticity if there is some lack of knowledge about one's ultimate tax status. We pay particular attention to these questions in our robustness checks. Although our data are repeated cross-sections, we have information on year $n - 1$ taxable income, and we therefore control for tax status in adjoining years. The fraction of households changing status in our sample is very stable over time and equal to 25 percent. In order to check the sensibility of our results to the reaction of these households, we add a dummy variable for those who shifted from a nontaxable group in year $n - 1$ to a taxable group in year n, and another dummy variable for households that shifted from a taxable group in year $n - 1$ to a nontaxable group in year n. We also investigate the effect on our estimated elasticities of removing people changing tax status from the sample.

Finally, taxpayers may anticipate price changes or partly shift donations over time, and our baseline identification strategy may capture these effects in the estimated price elasticity. We also investigate this question in the robustness section following the methodology of Bakija and Heim (2008) by introducing lagged and future changes in the log price of contributions.

Figure 1 offers the first graphical evidence of the evolution of gifts among taxable and nontaxable groups before the tax credit rate was increased in 2003, after the tax credit rate was increased a first time in 2003, and after it was increased a second time in 2005. Noticeably, the distribution of gifts seems to have shifted twice for taxable households, first after 2003, and then again in 2005–2006. The distribution of gifts remains fairly stable over time for nontaxable households. The intrinsic effect of an increase in the tax credit rate can be estimated by comparing every quantile of the distribution of contributions before and after the two tax reforms for the treatment and the control group. Our estimates extend this graphical distributional analysis to a censored quantile regression model with control covariates.

[21] Disposable income is defined as income minus income tax. Since it does not take into account the tax credit for contributions, disposable income is not endogenous to contributions made.

B. *Three-Step Censored Quantile Regression Estimation*

Among all taxable French households, the fraction of taxpayers reporting a gift to charities is about 20 percent. In our subsample of taxable and nontaxable households, this fraction is about 12 percent as shown in Figure 1. Dealing properly with the censoring process is therefore of considerable importance for empirical estimation. Some studies have investigated the question of censoring on US data using traditional Tobit models (Randolph 1995) or nonparametric censored regression models (like Bradley, Holden, and McClelland (2005) on cross-sectional data from the US Consumer Expenditure Survey). We use a semi-parametric estimation technique to deal with censoring, relying on a three-step censored quantile regression estimator proposed by Chernozhukov and Hong (2002). Quantile regressions also enable us to pay attention to the heterogeneity of giving behaviors. In most studies, where the log-log specification is adopted, homogeneity is de facto assumed. However, this assumption might not hold, as some studies have shown that price elasticities and income elasticities could vary with the type of contributors, and be, for example, quite different among rich and poor taxpayers (Bakija and Heim 2008).

When dealing with censored data, as is the case with contributions left-censored at 0, the OLS estimator is inconsistent. Tobit estimation may solve the censoring problem, but it relies on restrictive distributional assumptions that may prove invalid, particularly if censoring is heavy. Here we implement a censored quantile regression estimation technique that has the advantage of being more flexible than parametric estimation techniques like the Tobit model. This strategy has two main advantages over the Tobit model: it is distribution-free, and allows for heteroscedasticity. The basic intuition is that the conditional quantile of the distribution of gifts is unaffected by the censoring mechanism. This is the reason why we can obtain a consistent estimation without specifying a complete parametric distribution of the error term, which is impossible when one relies on the conditional mean of the distribution (as is the case in the Tobit model).

To understand the functioning of the three-step censored quantile regression model, it is useful to begin with explaining the standard quantile regression model without censoring. A quantile regression model simply consists of expressing the quantile of the distribution of the dependent variable as a linear function of some covariates X. Here, our dependent variable is gift G^*, and we can express the τ-*th* quantile of the distribution of gifts as

$$Q_{G^*|X}(\tau) = X'\beta(\tau).$$

Note that parameters β are different for each quantile of the distribution, and this is the reason why we index them by τ. The distributional effect of the covariates X on the dependent variable are thus given by the way the parameters $\beta(\tau)$ vary with τ. The estimation of the parameters $\beta(\tau)$ is based on the fact that the τ-*th* quantile of the distribution of the dependent variable is the solution of the following minimization problem:[22]

$$\text{Min}_\beta \sum_{i=1}^{n} \rho_\tau(G_i^* - X_i'\beta), \tag{3}$$

[22] See Roger Koenker (2005).

where observations are indexed by the subscript i, and ρ_τ is a check function defined as

$$\rho_\tau(G_i^* - X_i'\beta) = \begin{cases} \tau\ (G_i^* - X_i'\beta) & \text{if } G_i^* > X_i'\beta \\ (\tau - 1)\ (G_i^* - X_i'\beta) & \text{if } G_i^* \leq X_i'\beta. \end{cases} \tag{4}$$

The principle of this check-function is to weight by τ positive errors $(G_i^* > X_i'\beta)$ and by $(\tau - 1)$ negative errors $(G_i^* \leq X_i'\beta)$.[23]

Because of censoring of gifts at 0, we only observe $G = G^*$ if $G^* > 0$, and $G = 0$ if G^* is censored. This yields the censored quantile regression model

$$Q_{G|X,C}(\tau) = \max(X'\beta(\tau), 0), \tag{5}$$

where 0 is the censoring point, and C is an indicator for being censored. The most straightforward estimator of β would be to replace the linear form in 3 by the partially linear form:

$$\text{Min}_\beta \sum_{i=1}^{n} \rho_\tau(G_i - \max(X_i'\beta(\tau), 0)). \tag{6}$$

However, this estimator proposed by James L. Powell (1986) suffers from very low computational efficiency, because linear optimization techniques deal uneasily with partially linear constraints. The convergence of the Powell estimator is quite infrequent, especially with large datasets and numerous regressors. This is the reason why it has not experienced a significant development in the empirical literature. Many authors have proposed amendments to this original model, leading to more practical estimators.[24] The three-step version of censored quantile regression models proposed by Chernozhukov and Hong (2002) relies on structured modeling restrictions imposed on the censoring probability to get rid of the partially linear constraints in equation (6). These restrictions render this three-step estimator easily computable, while preserving the main advantages of censored quantile regression, namely, the heteroscedasticity and distribution-free character.

The idea of the three-step estimator proposed by Chernozhukov and Hong (2002) is to construct an iterated algorithm that works in the following way. It first selects a subset of observations for which the conditional quantile is in the observed part of the distribution. For these observations, a consistent estimator of $\beta(\tau)$ can be computed by running a standard quantile regression. The resulting estimates can be used to select a more refined subsample of uncensored observations, and, again, compute the quantile regression. Chernozhukov and Hong (2002) show in Monte Carlo simulations that the method leads to an efficient estimator after only two recomputations of the quantile regression.

[23] When $\tau = 0.5$ (median), the program in equation (3) is the minimization of the sum of the absolute value of errors. Overall, quantile regression amounts to minimizing a weighted average of the absolute value of residuals, whereas standard OLS minimize the sum of squared residuals.

[24] See for instance Moshe Buchinsky and Jinyong Hahn (1998) among others.

The principle of the three-step censored regression estimator is therefore to begin by selecting a subset of observations for which $X_i'\beta(\tau) > 0$. We select these observations by estimating a propensity score of not being censored $h(X_i) = P(G^* > 0 \mid X_i)$, and taking the observations for which $h(X_i)$ is strictly greater than $(1 - \tau)$. Intuitively, this ensures that for the selected observations, the fraction of observations with $G > 0$ is superior to $(1 - \tau)$ so that the conditional τ-*th* quantile exists and is above the censoring point. This first step is carried out by estimating a probability model of not censoring:

$$\eta_i = p(X_i'\lambda) + \varepsilon_i, \tag{7}$$

where η_i is the probability that gifts are positive. In our study, we use a simple logit to model the probability of giving, with the set of explanatory variables that are used in the quantile regression. Since our estimation of the true propensity score is possibly misspecified, we do not select all those observations with $p(X_i'\hat{\lambda}) > 1 - \tau$, but we select the observations that have

$$p(X_i'\hat{\lambda}) > 1 - \tau + c,$$

where c is a trimming constant between 0 and τ.[25]

The next step consists of running a standard quantile regression estimation on the subset $J(c)$ selected in step 1:

$$\mathrm{Min}_\beta \sum_{i \in J(c)} \rho_\tau(G_i - X_i'\beta_0(\tau)). \tag{8}$$

The estimate $\beta_0(\tau)$ of $\beta(\tau)$ is consistent, but not efficient because $J(c)$ is not the largest subset of observations in which $h(X_i) > 1 - \tau$. To get the largest subset of observations with $X_i'\beta(\tau) > 0$, we use the fact that $\hat{\beta}_0(\tau)$ is consistent, and we select all observations that have covariates X_i such that $X_i'\hat{\beta}_0(\tau) > 0$.[26] This step asymptotically selects all the observations with $X_i'\beta(\tau) > 0$, which brings efficiency to the third step.

In the third step, we simply run a quantile regression estimation on the observations selected during the second step. We then obtain a consistent and efficient estimation $\hat{\beta}_1(\tau)$ of $\beta(\tau)$. For each defined conditional quantile, the estimated coefficient $\hat{\beta}_1(\tau)$ represents the marginal effect of a change in the logarithm of the price on the logarithm of the conditional quantile of gift: it can be directly interpreted as a price elasticity.

[25] In practice, we choose c so that we can control the size of discarded observations from our subset $J(c) = \{i : p(X_i'\hat{\lambda}) > 1 - \tau + c\}$. The rule we follow is to select c so that: $\#J(c)/\#J(0) = 90$ percent, where $J(0)$ denotes the subset J, where $c = 0$. Chernozhukov and Hong (2002) demonstrate that J does not need to be the largest subset of observations where $h(X_i) > 1 - \tau$.

[26] In practice, we select observations such that $X_i'\hat{\beta}_0(\tau) > 0 + \xi$, where ξ is a small positive number (with $\xi_n \to 0$).

We apply this three-step procedure to model (2) presented above. Because the dependent variable is the logarithm of gifts ($\ln(gift)$), and since many households do not give to charities, we give every household an extra dollar of gifts so that $\ln(gift)$ is defined for every taxpayer and ranges from 0 to ∞. This method is common in previous literature on the subject,[27] but given the curvature of the log function, one may be concerned that the elasticity found for very small gifts is affected by this procedure. We investigate this issue in the robustness check section by setting the censoring point at 10 euros instead of 0.

Computation of standard errors is done via nonparametric bootstrapping. We randomly draw samples of observations from the data, allowing for a very general form of heteroscedasticity. Still, our computation of standard errors assumes that error terms are independent over time. As pointed out by Marianne Bertrand, Esther Duflo, and Sendhil Mullainathan (2004), the serial correlation of errors within group, over time, may cause a downward bias in the standard errors in difference-in-difference estimates. There is, unfortunately, no easy way to solve this problem in our censored quantile regression framework. In particular, there is no guidance on the best way to correct for the group $\times$ time serial correlation when the number of groups is small, as in our case. Block bootstrapping, which is a way to correct for serial correlation when the number of groups is large,[28] often does not work when the number of groups is small.[29] In order to assess the severity of the problem of serial correlation, we run OLS estimations with standard methods of correction of this problem (as described in Bertrand, Duflo, and Mullainathan 2004) and find no loss of significance for the estimated price elasticity in the OLS case.[30] Moreover, we find very little correlation of residuals over time in the OLS case, suggesting that serial correlation is not a severe problem in our data.

IV. Results

A. *Baseline Estimates*

In this section, we present the baseline results and discuss the overall effect of the 2003 and 2005 reforms on charitable giving. Results are displayed in Figure 2, which graphically represents the quantile coefficient estimates, with the dashed line representing the 95 percent confidence interval calculated from bootstrapped standard errors.[31] Note that because of heavy censoring, it is not possible to robustly estimate quantile coefficients below quantile 0.9 for the whole sample.

First, it appears that the overall effect of tax reforms is small. For all defined quantiles, the coefficient estimate ranges from -0.2 to -0.6, which is well below the elasticity that would be required for the credit rate to be optimal without crowding

[27] See Andreoni (2006).

[28] It has been used for the estimation of quantile treatment effects in panel data (Marianne P. Bitler, Jonah B. Gelbach, and Hilary W. Hoynes (2006, 2008)).

[29] In Monte Carlo simulations presented in Bertrand, Duflo, and Mullainathan (2004), block bootstrapping performs poorly in the OLS case when the number of groups is small.

[30] Results are available upon request.

[31] Tables presenting the results are displayed in the Appendix.

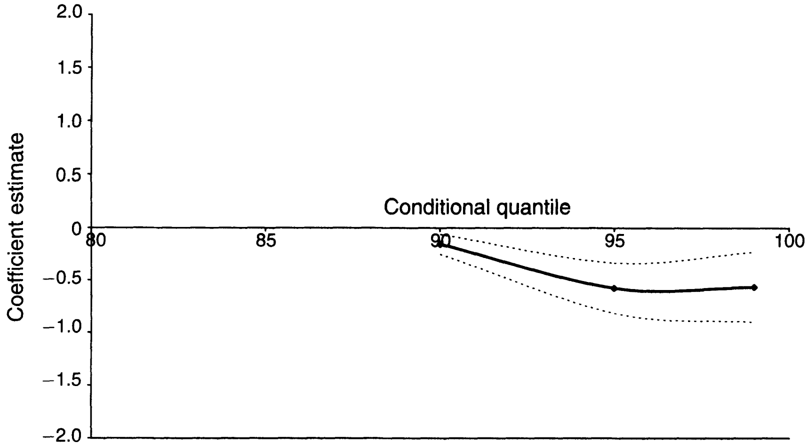

FIGURE 2. ESTIMATED PRICE ELASTICITY OF CHARITABLE CONTRIBUTIONS FROM QUANTILE REGRESSIONS

Notes: Results from the three-step censored quantile regression. Dashed lines represent the 95 percent confidence interval calculated from bootstrapped standard errors (200 replications). A 1 percent increase in the price of contributions reduces by 0.16 percent the ninetieth conditional quantile of the distribution of charitable contributions.

out. The effect of the reforms is also heterogenous as coefficients vary across quantiles of gifts. The highest quantiles (ninety-fifth and ninety-ninth percentiles) seem to react more to the reforms. If the tax credit variation had led to homogenous behavioral responses, the whole distribution would have shifted equally, and the coefficient estimate would be equal across all quantiles. The results can be interpreted as an indication that the reforms led large contributors to contribute more while smaller contributors did not significantly change their habits. It is also interesting to compare our estimate with the OLS and the Tobit estimates, as shown in Table A4 in the Appendix. Because of heavy censoring, the OLS estimate is biased, and leads to a lower estimate of the elasticity than those obtained with quantile regressions. The OLS estimate (−0.161) is comparable to the estimate on the lower quantile, but smaller than the estimates for higher quantiles. The Tobit estimate corresponds to a marginal effect for the conditional mean of the observed gifts of −0.4, which is closer to the estimates of the higher quantiles. The existence of important distributional effects is therefore a drawback for the traditional Tobit estimation in the case of heavy censoring because Tobit estimation extrapolates to the whole distribution the aspect of the distribution on a few uncensored observations. In contrast, quantile regressions do not need to consider the shape of the distribution below the censoring threshold. Our findings regarding the heterogeneity of the effect support our estimation strategy.

The quantile regression estimates do not provide a simple figure of the mean elasticity directly comparable with previous estimates. Unfortunately, the calculation of mean effects requires the simulation of a counterfactual conditional distribution of gifts that cannot be done in our setting because we do not know the effect of the tax incentives for the conditional quantiles of gift that are below the censoring point.[32] Overall, our estimated elasticities are never inferior to -0.6 on any conditional quantile, which means that the mean elasticity cannot be above that level. Therefore, our estimates stand in the lower range of the elasticities found in US data. Part of the differences between our estimates and the US elasticities may also be due to our focus on households in the middle and upper-middle of the income distribution, whereas US studies tend to be done on richer households, which may respond more to tax incentives.

B. *Robustness Checks*

Time Shifting.—As previously mentioned, people may anticipate price changes, and therefore partly shift contributions over time in order to take advantage of a higher tax credit rate. To make sure that our baseline results are not driven by these time shifting effects, we present results of a specification that introduce lagged and future changes in the log price of contributions.

The specification becomes:

$$\text{(9)} \qquad \ln(gift)_i = \sum_j \alpha_j \times group_{ji} + \beta_1(taxable_i) \times (\ln(1 - t_n)) + \beta_2(taxable_i) \times (\underset{n-1,n}{\Delta} \ln(1 - t)) + \beta_3(taxable_i) \times (\underset{n,n+1}{\Delta} \ln(1 - t)) + \sum_n \gamma_n Year_{ni} + \sum_k \theta_k X_{ki} + \epsilon_i,$$

where subscript n stands for year n, t_n is the tax credit rate at date n, and $\underset{n-1,n}{\Delta} \ln(1 - t)$ and $\underset{n,n+1}{\Delta} \ln(1 - t)$ stand for the lagged and forward difference in log price of contributions.[33] β_1 identifies the (long-term) elasticity of contributions with respect to price, controlling for optimization behaviors that involve shifting contributions from one year to the other due to anticipated variations in the tax credit rate. If households optimize their charitable giving over time, we expect β_2 to be negative and β_3 to be positive. In case of a reduction in price between year $n - 1$ and year n ($\underset{n-1,n}{\Delta} \ln(1 - t) < 0$), households that re-optimize their approach to giving will delay their contributions in year $n - 1$ and report them in year n, thus increasing $\ln(gift)$ in year n, ceteris paribus. Conversely, an anticipated price reduction between year n and year $n + 1$ will cause people to report lower contributions in year n in order to take advantage of a higher tax credit rate in year $n + 1$.[34]

[32] This problem arises even if we focus on mean effects conditionally on giving. For example, if the eightieth quantile is defined for high income households, the effect on the eightieth quantile of contributions cannot be estimated because of a lack of support of the other covariates. We would need to make strong assumptions on the effect for these households in order to calculate a mean effect on donors.

[33] $\underset{n-1,n}{\Delta} \ln(1 - t) = \ln(1 - t_n) - \ln(1 - t_{n-1})$ and $\underset{n,n+1}{\Delta} \ln(1 - t) = \ln(1 - t_{n+1}) - \ln(1 - t_n)$.

[34] In the specification, we assume that households have the same tax status in year $(t - 1)$, t, and $(t + 1)$.

TABLE 2—SENSITIVITY ANALYSIS

Variables	Quantile $q = 0.9$	$q = 0.95$	$q = 0.99$
Baseline estimates			
tax. × ln(1 − t)	−0.155***	−0.576***	−0.566***
	(−0.251 to −0.060)	(−0.818 to −0.334)	(−0.902 to −0.229)
Time shifting			
tax. × ln(1 − t)	−0.186***	−0.562***	−0.623***
	(−0.279 to −0.093)	(−0.868 to −0.256)	(−1.027 to −0.218)
tax. × $\Delta_{n-1,n}$ ln(1 − t)	0.0201	−0.155	0.405
	(−0.136 to 0.177)	(−0.837 to 0.528)	(−0.331 to 1.141)
tax. × $\Delta_{n,n+1}$ ln(1 − t)	−0.127***	−0.798***	−0.463
	(−0.306 to −0.050)	(−1.406 to −0.190)	(−1.063 to 0.138)
Mobility across groups			
tax. × ln(1 − t)	−0.176***	−0.607***	−0.598***
	(−0.262 to −0.091)	(−0.846 to −0.368)	(-0.908 to −0.287)
nontax → tax	−0.0396***	−0.285***	−0.139***
	(−0.065 to −0.014)	(−0.379 to −0.191)	(−0.223 to −0.055)
tax → nontax	0.0768***	0.411***	0.246***
	(0.038 to 0.115)	(0.319 to 0.503)	(0.145 to 0.348)
Exclusion of households changing group			
tax. × ln(1 − t)	−0.296***	−1.017***	−0.884***
	(−0.456 to −0.136)	(−1.362 to −0.673)	(−1.226 to −0.542)
Censoring set at 10 euros			
tax. × ln(1 − t)	−0.0745***	−0.308***	−0.565***
	(−0.128 to −0.021)	(−0.477 to −0.140)	(−0.902 to −0.227)

Notes: Three-step censored quantile regression parameters estimates. Ninety-five percent confidence intervals in parentheses, calculated using bootstrapped standard errors (200 replications).

***Significant at the 1 percent level.

**Significant at the 5 percent level.

Results reported in Table 2 show no evidence that optimizing behavior may occur. The signs of β_2 and β_3 tend to suggest that households' reactions are delayed, and the effects of the past price variations are not statistically significant. Moreover, introducing these controls for lagged and forward variations in price does not significantly affect the value of the (longer-term) elasticity of contributions with respect to price.

Mobility Across Treatment and Control Groups.—Another important assumption of our identification strategy lies in the stability of control and treatment groups over time. Even though the fraction of households in our sample changing status (from taxable to nontaxable or vice versa) is very stable over time, and equal to 25 percent, this may affect our estimates in two opposite ways. On the one hand, the estimated price elasticity of gifts β in (2) may mix transitory and permanent price effects because households that are taxable, but were nontaxable the year before, may optimize the timing of their gifts to take advantage of the tax credit. On the other hand, the estimated effect of price β may underestimate the true elasticity if there is some lack of knowledge about ultimate tax status. Since we have information on taxable income in year $n - 1$, we can control for tax status in adjoining years. We add a dummy for households that shift from a nontaxable group in year $n - 1$ to a taxable group in year n, and another dummy variable for households that shift from a taxable group in year $n - 1$ to a nontaxable group in year n. Results are reported in Table 2 and show that, contrary to the assumption that people optimize the timing of their gift when moving from one status to the other, people tend to give according to their previous tax status. Nontaxable households that were previously taxable tend to give more than nontaxable households, ceteris paribus, and the opposite holds for taxable households that were previously nontaxable. This suggests that some households may lack information about their ultimate tax status and thus their right to claim the charitable tax credit. To investigate the magnitude of this potential attenuation bias, we run our baseline specification and remove households that change tax status from the sample. Results are reported in Table 2 and suggest that there is some attenuation bias, mainly affecting the bottom of the distribution of contributions. The estimated elasticity of contributions is larger for the restricted sample, but mainly on quantile 0.9 to 0.95.

Log-Log Specification.—In the log-log specification adopted here, we follow the standard procedure of rescaling the dependent variable as $\ln(gift + 1)$ so that the dependent variable is defined for all households and ranges from 0 to ∞. Given the curvature of the log function, one may be concerned that the elasticity found for very small gifts is affected by this procedure. To ensure that our results are robust to this procedure, we check that setting the censoring point at 5 or 10 euros instead of 0 did not significantly alter our estimates. We run our three-step censored quantile regression estimator with $\ln(gift)$ as a dependent variable if $gift > 10$, and consider the observation to be censored otherwise. The results are reported in Table 2 and confirm that our normalization procedure does not affect the estimated elasticity of the baseline strategy.

V. Conclusion

This paper uses two recent reforms that increased tax deductions for charitable contributions in France to provide new estimations of the effect that these fiscal incentives have on gifts. We show that the increase in fiscal incentives toward charitable giving did not lead to the expected increase in gifts in our sample of households. The estimated elasticities, between -0.2 and -0.6, are in the lower range of the elasticities found for US data, but are consistent with other results in the literature on samples containing middle income rather than high income households. These estimated elasticities imply that the increase in charitable giving caused by the higher tax credit was smaller than the foregone revenue for the government.

We study the heterogeneity of responses among the distributions of gifts using a three-step censored quantile regression estimator proposed by Chernozhukov and Hong (2002) and find evidence of heterogenous response according to the level of gifts. More generous donors appear to react more to tax incentives than smaller donors, suggesting that tax incentive schemes with higher rates for large gifts might be more efficient than a unique rate. Overall, these results suggest that the actual French credit rate can only be justified if crowding out between private and public contributions is large, or if private funds are much more efficiently used than public funds.

Appendix: Tables

Table A1—Descriptive Statistics of the Estimation Sample by Tax Status

Year	Tax status	Mean disposable income	Percentage of donors	Mean gift among donors	Mean *Quotient Familial*	Observations
1998	Nontaxable	18,232	13	131	2.2	18,266
1998	Taxable	17,731	11	121	1.7	35,638
1999	Nontaxable	18,424	13	125	2.2	25,415
1999	Taxable	17,945	11	130	1.6	32,441
2000	Nontaxable	18,633	13	111	2.1	16,831
2000	Taxable	18,204	11	138	1.6	29,051
2001	Nontaxable	18,868	13	134	2.1	16,322
2001	Taxable	18,524	11	133	1.6	28,113
2002	Nontaxable	18,837	13	130	2.1	21,855
2002	Taxable	18,614	12	153	1.6	34,919
2003	Nontaxable	18,699	13	130	2.1	22,519
2003	Taxable	18,436	11	148	1.6	31,385
2004	Nontaxable	18,720	13	114	2.1	20,230
2004	Taxable	18,469	13	144	1.6	27,782
2005	Nontaxable	18,746	13	146	2.1	19,686
2005	Taxable	18,721	12	157	1.6	26,024
2006	Nontaxable	19,015	13	157	2.0	21,556
2006	Taxable	19,049	12	193	1.6	26,752

Notes: Contributions and income are expressed in 2004 euros. *Taxable* is defined as being eligible for the charitable tax credit. QF (*Quotient Familial*): Number of units given to the household to compute tax liability in the French family-splitting system.

Source: Authors' calculations from *Echantillons Lourds*

Table A2—Descriptive Statistics for the Selected Treatment and Control Groups, (*1998–2006*)

Tax status	*Quotient Familial*	Mean disposable income	Percentage of donors	Mean gift among donors	Observations
Nontaxable	1.5	15,108	13	146	55,841
Nontaxable	2	18,206	14	117	52,362
Nontaxable	2.5	21,350	14	136	26,788
Nontaxable	3	24,182	10	110	24,144
Nontaxable	4	28,053	11	118	20,007
Nontaxable	5	32,666	13	181	3,538
Taxable	1	14,219	5	171	110,016
Taxable	1.5	17,528	18	151	59,971
Taxable	2	21,017	18	141	45,878
Taxable	2.5	24,182	13	127	18,705
Taxable	3	28,100	13	126	25,042
Taxable	4	33,311	17	124	12,493

Notes: Contributions and income are expressed in 2004 euros. *Taxable* is defined as being eligible for the charitable tax credit. The higher percentage of donors in the *nontaxable* group is due to composition effects of the different groups in the calculation of the mean. QF (*Quotient Familial*) corresponds to the number of units given to the household to compute tax liability in the French family-splitting system.

Source: Authors' calculations from *Echantillons Lourds*

Table A3—Baseline Results. Three-Step Censored Quantile Regression Estimates. Dependent Variable: Log of Contributions

	Quantile		
Variables	$q = 0.9$	$q = 0.95$	$q = 0.99$
$\ln(1 - t) \times$ taxable	−0.155***	−0.576***	−0.566***
	(−0.251 to −0.060)	(−0.818 to −0.334)	(−0.902 to −0.229)
ln (disposable income)	1.288***	3.001***	1.534***
	(1.032 to 1.545)	(2.736 to 3.267)	(1.309 to 1.760)
Age	0.0219***	0.0805***	0.0431***
	(0.018 to 0.026)	(0.077 to 0.084)	(0.040 to 0.046)
Single	0.0842*	−0.105	0.227***
	(−0.007 to 0.175)	(−0.266 to 0.056)	(0.0762 to 0.378)
Divorced	−0.331***	−0.0202	−0.0523
	(−0.406 to −0.256)	(−0.140 to 0.099)	(−0.166 to 0.062)
Married	−0.368***	−0.496***	−0.160*
	(−0.439 to −0.298)	(−0.750 to −0.242)	(−0.334 to 0.014)
Wage earner	−3.407***	−0.751***	−0.474***
	(−3.597 to −3.216)	(−0.851 to −0.652)	(−0.569 to −0.380)
Intercept	−9.475***	−29.74***	−11.80***
	(−12.24 to −6.71)	(−32.24 to −27.24)	(−13.98 to −9.621)
Observations	400,881	400,881	400,881

Notes: Three-step censored quantile regression parameters estimates. 95 percent confidence intervals in parentheses, calculated from bootstrapped standard errors (200 replications). Dummy variables for each income × family size group and year dummies are also included in the regressions. Marital status is "widowed."

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Table A4—Comparison between Quantile Regression, OLS, and Tobit

	$q = 0.9$	$q = 0.95$	$q = 0.99$
Quantile regression (3-steps)			
tax. $\times \ln(1 - t)$	−0.155***	−0.576***	−0.566***
	(−0.251 to −0.060)	(−0.818 to −0.334)	(−0.902 to −0.229)
OLS			
tax. $\times \ln(1 - t)$		−0.161***	
		(−0.235 to −0.088)	
Tobit (marginal effect)			
tax. $\times \ln(1 - t)$		−0.40 ***	
		(−0.448 to −0.361)	

Notes: Ninety-five percent confidence intervals for three-step censored quantile regressions calculated from boostraped standard errors (200 replications). Confidence intervals for OLS calculated from clustered robust standard errors at the group level. OLS regressions are performed on the whole sample, including households who do not give. The coefficient reported in the Tobit regression is the marginal effect on the conditional mean of the observed variable.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

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