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# Local Public Goods and the Crowding-out Hypothesis: Evidence from Civic Crowdfunding

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## Abstract

We study civic crowdfunding campaigns, which leverage online platforms to raise funds for local public goods. We investigate ``crowding-out'' along two dimensions. We test whether an individual's contributions to a campaign are diminished by (1) the availability of another charitable cause and (2) contributions from other donors. We find strong robust evidence of a negative relationship between donating to a specific campaign and donating to the civic crowdfunding platform. Crowding out across charitable causes is most prevalent among donors who live far away from the crowdfunding campaign's location and among donors living in low-income neighborhoods. We find limited and inconclusive evidence of crowding-out across donors. The findings represent an initial empirical exploration of crowding out in civic crowdfunding.

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# 1 Introduction

Crowdfunding has changed the landscape of fundraising and charitable giving. Kickstarter and Indiegogo are among the best-known crowdfunding platforms, having raised over $5 billion from diffuse donors for myriad projects. *Civic* crowdfunding is a unique type of crowdfunding that garners funds for civic causes, such as urban renewal, neighborhood green space, and community events. Civic crowdfunding is a novel and increasingly prevalent mechanism for providing local public goods, and it has been championed as a more participatory form of planning that can alleviate inequalities in access to local public amenities.

We investigate donation behavior in civic crowdfunding campaigns with a focus on "crowding out" along two dimensions. We use a novel dataset from a leading civic crowdfunding platform to examine whether an individual's contributions to a campaign are diminished by (1) the availability of another charitable cause and (2) contributions from other donors. Each of these channels sheds light on different dimensions of crowding out. The former touches on issues of competition (or synergies) between charitable causes by revealing how contributions are shaped by the presence of multiple outlets for giving. The latter addresses the perennial issue of strategic crowding out, a subject of great interest to academics and practitioners alike. Classic public good models predict extensive crowding out (Bergstrom et al., 1986; Andreoni, 1993), as own contributions and others' contributions to the public good enter the utility function as perfect substitutes. However, as noted by Andreoni (1989), these models fail to predict patterns of behavior observed in the real world. By contrast, models of impure altruism and warm glow, whereby donors derive private utility from giving, align better with observed behaviors. Interestingly, impure altruism may lead to crowding *in* (Kotchen and Wagner, 2019), whereby one's contribution to the public good encourages further contributions from others. Likewise, more recent models stemming from the behavioral economics literature, such as reciprocity (Falk and Fischbacher, 2006), social norms (Shang and Croson, 2009), or reputational concerns (Elfenbein et al., 2012), may also produce crowding in.

Thus, our study addresses central questions surrounding the private provision of public goods and offers some of the first empirical economics research on civic crowdfunding. In this light, civic crowdfunding is especially relevant to study because many campaigns expressly seek to leverage these behavioral motives to garner contributions. They have an explicit focus on local communities and participation, and they frequently showcase lists of donors and provide information on cumulative donations—all of which appeal to social motivations but would be overlooked in the neoclassical model. Our work also provides insights on effective strategies and design principles for fundraising through civic crowdfunding campaigns.

We find that donors who contribute to the civic crowdfunding platform donate less to individual campaigns. This result suggests crowding out across charitable causes, and that there may be a tradeoff between the needs of the crowdfunding platform and the needs of individual campaigns. Crowding out across charitable causes is consistent across all modeling specifications, including ones with donor and campaign fixed effects. We present suggestive evidence of a negative relationship between the cumulative donations to campaigns and the size of subsequent donations, but the parameter is not consistent across modeling specifications. Additionally, inference on these effects is complicated by selection in timing. That is, the most motivated donors, often friends and family, typically donate in the early stages of the campaign.

This research contributes to the growing literature on the economics of crowdfunding. Most work focuses on traditional private crowdfunding (Burtch et al., 2013; Belleflamme et al., 2014; Pitschner and Pitschner-Finn, 2014; Agrawal et al., 2015). Our work instead focuses on addressing civic crowdfunding, something that few others have done. Along these lines, there are several studies that examine behavior on DonorsChoose, a platform that raises (predominantly local) funds for teachers in need of school supplies. Koning and Model (2013) examine how seed contributions affect subsequent donations and the success of these campaigns. They find that moderately sized seed contributions ($40) spur further donation activity compared to control campaigns, but smaller seed amounts ($5) lead to lower rates of campaign success, which attests to the importance of social influence from early actors.[1] Meer (2014) also uses DonorsChoose, in this case to investigate how price affects charitable giving. Our work is unique in studying crowding out for civic crowdfunding, which is especially important because local public goods—the focus of civic crowdfunding—may have different patterns of crowding out than other charitable causes.

Our work is also related to a large literature studying crowding out in charitable giving (Bergstrom et al., 1986; Andreoni and Payne, 2011; Reinstein, 2011; Borgloh et al., 2013; Werfel, 2018). We extend existing work by examining two distinct dimensions of crowding out in civic crowdfunding. However, because we do not exploit random or quasi-random variation to identify our parameters of interest, we caution against a causal interpretation of our results. The results highlight the need for further research to causally identify crowding effects—and their underlying behavioral mechanisms—in civic crowdfunding.

# 2 Data

We study campaigns listed on the civic crowdfunding platform, ioby. Like many crowdfunding sites, ioby provides a space where campaign leaders can raise funds from donors across the world. In Figure 1, we show the information visible to a donor via ioby's home page, the primary campaign page, and the donor tab of the campaign page. The ioby home page provides a brief blurb of the campaign as well as a summary of the funding goal and amount of funds secured to date. The primary campaign page offers more detailed information on the project being funded, including the location, the campaign deadline along with a countdown of days remaining, funding progress, and a description written by the campaign leader. Donors can also see detailed donor activity, as shown in the third panel of Figure 1, which displays the name and number of donors who have given thus far.

As a non-profit seeking to maximize funds flowing to campaigns, ioby charges a relatively small fee for their services. They charge 3% of total funds raised, as opposed

[1] In related work, Parker (2014) uses a simulation model to study the role of information cascades in the success or failure of crowdfunding campaigns.

Figure 1: Crowdfunding Campaign on ioby's platform


Note: From left to right the images show the view from the home page, the primary campaign page, and the donor tab of the campaign page.

to 8–10% charged on Kickstarter, a leading for-profit platform. Because of the small size of these service fees, much of ioby's administrative costs are funded through grants and foundation support and through optional gratuities (which we will call "tips") that donors make when contributing to a campaign. Thus, prospective donors are confronted with a budget allocation decision: how much to contribute to the campaign itself versus tips to support ioby's operation.

Thus, we are interested in investigating two dimensions of crowding out. First, do tips to ioby crowd out campaign contributions? This is an important empirical question, because it will reveal the extent to which there is conflict between the funding goals of campaign leaders and of ioby. Second, how do prior contributions to a campaign influence subsequent contributions? This question addresses strategic crowding out and the issue of free-riding in public goods provision.

To answer these questions, we obtained primary data from ioby on campaigns completed between April 2010 and May 2016. We have donation histories and addresses for each campaign. We also have data on each specific donation, including the amount contributed to the campaign, the tip amount, and the address of the donor.

In addition to our primary data, we calculate distances from donors to campaigns.[2] We merge census demographics for donors at the block level using the American Community Survey (2010-2014) and the Federal Communication Commission's geocoding API.[3] We drop observations that we cannot geocode, including those that are at a PO Box, as many of these were philanthropic foundations as opposed to individuals. We also drop observations for donors that contribute to more than 10 campaigns, as these are atypical donors.

Brent and Lorah (2019) provide a more thorough description and analysis of the data, so we focus on the variables relevant for crowding out: donations, tips, cumulative donations, number of donors, distance between donor and campaign, and donor census block income. The summary statistics are presented in Table 1. The average donation is $85 and the median donation is $35, highlighting the prevalence of small donations in civic crowdfunding. Roughly 60% of donors provided a tip to ioby when contributing to a campaign. The average tip was slightly over $5, and the average tip conditional on tipping was $9.

[2]Addresses were geocoded to acquire geographic coordinates using R's Data Science Toolkit.

[3]A census block is a geographic area consisting of 600-3000 people. There are over 200,000 block groups in the U.S., representing a relatively fine geographic resolution.

**Table 1: Summary Statistics**

| Statistic | Mean | St. Dev. | Median | Min | Max | N |
|---|---|---|---|---|---|---|
| Donation ($) | 85.03 | 288.61 | 35 | 1 | 20,000 | 15,724 |
| Ioby Tip (%) | 0.60 | 0.49 | 1 | 0 | 1 | 15,724 |
| Ioby Tip ($) | 5.31 | 13.21 | 2 | 0 | 907 | 15,724 |
| Cumulative Donations (%) | 4.51 | 8.62 | 1.75 | 0.00 | 90.25 | 15,724 |
| Distance (miles) | 370.52 | 798.67 | 8.11 | 0.00 | 10,167.05 | 15,709 |
| Median HH Income ($) | 74,314 | 40,581 | 65,833 | 4,402 | 250,001 | 15,498 |

# 3 Empirical Model

We investigate how donations to a campaign are associated with (1) direct donations to the ioby platform and (2) the cumulative value of donations to that campaign. We specify the following regression equation:

$$Donation_{ip} = \alpha + \beta_1 IobyTip_{ip} + \beta_2 cDonations_{ip} + \beta_3 X_{ip} + \varepsilon_{ip}, \tag{1}$$

where $Donation_{ip}$ is individual $i$'s contribution to campaign $p$ in dollars; $IobyTip_{ip}$ is a dummy variable equal to one if individual $i$ gave a tip to ioby when donating to campaign $p$; $cDonations_{ip}$ is the cumulative value of donations (as a percentage of the funding goal) to campaign $p$ at the time of $i$'s donation; and $X_{ip}$ is a vector of controls relevant to individual $i$ and/or campaign $p$. Our primary specification focuses on the binary decision to tip, but we also analyze the value of the tip.

We run several variations on this base specification, with different constellations of control variables, interaction terms, and campaign and donor fixed effects. The propensity to tip and the cumulative donations are not randomly assigned. Therefore, our estimates should not be interpreted as causal; rather they provide an initial foray into crowding out in civic crowdfunding. While we do not have an experimental or quasi-experimental design to identify crowding effects, we are able to employ fine grain fixed effects to control for potential confounders. In particular, our most conservative specification includes both campaign and donor fixed effects. Therefore, we control for unobserved characteristics of both the campaign and the donor. The identifying variation relies on donors who contribute to multiple campaigns and therefore we can see how their donation changes as their tips change across different charitable campaigns.

### 3.1 Hypotheses

Our first hypothesis (H1) is that $\beta_1 < 0$: tips to ioby crowd out donations to the campaign. Tips may crowd out campaign donations if donors have a fixed budget for charitable giving or if they see the two as substitutable avenues for charitable giving. crowding out in this dimension is consistent with standard substitution effects or budget constraints from consumer theory.

Our second hypothesis (H2) is that $\beta_2 < 0$: prior donations to a campaign crowd out subsequent donations. Here, we may see classic (strategic) crowding out that is commonly discussed in public good theory and charitable giving. Because public goods are non-excludable, individual $i$'s marginal willingness to contribute decreases in others' contributions.

We test for heterogeneity in crowding out by interacting $IobyTip_i$ and $cDonations_{ip}$ with quintiles of (i) neighborhood income at the donor's address and (ii) distance between the donor's address and the campaign's address. We choose income as a potential modulator because donors with higher incomes will be less likely to face binding budget constraints, meaning that there may be a different relationship between tips and campaign donations for those individuals. Similarly, proximity to the campaign location is a proxy for the degree to which the campaign's project provides direct benefits to the donor; those who live at different distances from the project may therefore face different crowding out effects.

# 4 Results

## 4.1 Base Results

Table 2 shows results from our empirical model. The first column controls for distance from the donor to the campaign's project and donor's neighborhood income with dummies for each quintile of these variables. The third quintile is omitted so the effects should be interpreted as the impact on donations relative to the median distance and income.[4] The second column adds campaign fixed effects. The third column adds donor fixed effects and the fourth column incorporates both campaign and donor fixed effects. The third and fourth columns of Table 2 rely on within-donor variation, and therefore restricts the sample to donors that have made more than one donation. Overall 25.7% of the donations in the sample are from donors who have made more than one donation, and the mean number of donations is 1.55. It is possible that repeat donors are somewhat different than the typical donor, so although the donor fixed effects control for unobserved donor heterogeneity, the sample may not be representative. We do test for several differences in the sample of single donors compared to multiple donors. Donors who contributed to multiple campaigns live in slightly less wealthy neighborhoods with lower educational attainment and live closer to campaigns' projects to which they contributed relative to donors who only contributed to one campaign.[5,6]

In all specifications we find evidence to support H1. The coefficient on ioby tip is negative and highly significant. The results show that a donor who gives directly to ioby

[4]We used continuous controls as well and the effects are similar, but as seen in Table 2 the effects are highly nonlinear so we prefer the quintile specification.

[5]The difference in neighborhood income is roughly \$5000, the difference in the percentage who have a college degree or higher is 1%, and the average distance to campaigns' projects is 70 miles. All the average differences are statistically significant at the 5% level based on t-tests.

[6]It may seem counter-intuitive that donors from less wealthy neighborhoods contribute to more campaigns. For example, Ghosh et al. (2007) describe how lower-income individuals should be more likely to free-ride. However, those less wealthy donors are also likely to reside much closer to the projects of interest, so we suspect that the cause of this discrepancy is differences in proximity, and that the strength of effect is strong enough to be evident in spite of the fact that income would have an opposite, countervailing effect. As noted by Brent and Lorah (2019), projects tend to be cited in lower-income areas than donor locations. Furthermore, we should stress that our income data are at the neighborhood level rather than donor level, so it is possible that our sample is composed of higher-income people from low-income neighborhoods and/or lower-income people from high-income neighborhoods.

donates between \$32–\$55 *less* to the campaign depending on whether we include donor and project fixed effects. These results indicate *crowding out* across charitable causes. While our research design cannot pinpoint the mechanism behind this observation, we should emphasize that the role of donor types can only partially explain the negative association. Even when controlling for donor fixed effects, we continue to see a negative association between ioby tips and campaign donations. This further suggests that fundraisers may suffer from substitutability or competition when donors face multiple charitable causes.

Meanwhile, there is weak evidence of *crowding out* in support of H2. Donations are smaller when a larger percentage of the campaign is funded, consistent with strategic substitutability in public goods. However, this effect is not statistically significant in the presence of donor fixed effects. Moreover, the interpretation of cumulative donations is complicated and potentially confounded by selection. Highly motivated donors, such as friends and family, may donate in the early stages of a campaign (when cumulative donations are lowest) and also donate higher amounts.

Table 2 focuses on the correlation between the binary decision to tip and campaign donations. In Table 3, we also incorporate the size of the tip as an additional regressor. The interpretation of the tip amount is the effect of an additional dollar tipped to ioby on the size of the donation to the campaign. As shown in Table 3 the tip amount is positively associated with the size of the campaign donation conditional on having tipped a positive amount. However, compared to our initial results, the size of the binary tip variable increases in magnitude such that the average effect of tipping is consistent with the results in Table 2. The size of the tip may be associated with income effects or general philanthropic preferences. However, explanations that rely on donor type only tell part of the story; they cannot explain the relationship in columns (3) and (4). Here, we see that there remains a positive and significant relationship between donations and tip amount, even when including donor fixed effects.

## Table 2: Multidimensional crowding out

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Ioby Tip | $-54.351^{***}$ | $-47.445^{***}$ | $-36.651^{***}$ | $-32.019^{***}$ |
| | (4.723) | (4.655) | (8.546) | (9.445) |
| Cumulative Donations (%) | $-0.783^{***}$ | 0.325 | $-0.230$ | $-0.310$ |
| | (0.268) | (0.416) | (0.394) | (0.644) |
| Dist Q1 | $12.886^{*}$ | $14.352^{*}$ | | |
| | (7.402) | (8.283) | | |
| Dist Q2 | 4.498 | $-0.284$ | | |
| | (7.336) | (7.510) | | |
| Dist Q4 | 4.913 | 8.052 | | |
| | (7.320) | (7.592) | | |
| Dist Q5 | $12.410^{*}$ | 7.827 | | |
| | (7.356) | (8.353) | | |
| Income Q1 | $-6.102$ | $-6.470$ | | |
| | (7.460) | (7.417) | | |
| Income Q2 | $-12.310^{*}$ | $-10.701$ | | |
| | (7.387) | (7.264) | | |
| Income Q4 | $-1.534$ | $-0.075$ | | |
| | (7.356) | (7.204) | | |
| Income Q5 | $27.972^{***}$ | $18.872^{***}$ | | |
| | (7.301) | (7.232) | | |
| Campaign FEs | No | Yes | No | Yes |
| Donor FEs | No | No | Yes | Yes |
| Observations | 15,488 | 15,488 | 4,040 | 4,040 |
| Adjusted $R^2$ | 0.011 | 0.122 | 0.576 | 0.584 |
| *Note:* | $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ | | | |

## Table 3: Multidimensional crowding out with continuous tip amount

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Ioby Tip | $-108.085^{***}$ | $-99.207^{***}$ | $-75.989^{***}$ | $-73.870^{***}$ |
| | (4.819) | (4.747) | (8.861) | (10.059) |
| Tip Amount | $6.080^{***}$ | $5.827^{***}$ | $3.785^{***}$ | $3.747^{***}$ |
| | (0.178) | (0.174) | (0.302) | (0.363) |
| Cumulative Donations (%) | $-0.709^{***}$ | 0.358 | $-0.130$ | $-0.225$ |
| | (0.259) | (0.401) | (0.382) | (0.627) |
| Dist Q1 | 7.807 | 11.220 | | |
| | (7.140) | (7.987) | | |
| Dist Q2 | 4.302 | $-1.042$ | | |
| | (7.075) | (7.240) | | |
| Dist Q4 | $-1.559$ | 1.728 | | |
| | (7.062) | (7.322) | | |
| Dist Q5 | 6.039 | 5.250 | | |
| | (7.097) | (8.054) | | |
| Income Q1 | $-2.057$ | $-3.653$ | | |
| | (7.195) | (7.152) | | |
| Income Q2 | $-10.366$ | $-8.886$ | | |
| | (7.125) | (7.004) | | |
| Income Q4 | $-3.233$ | $-1.042$ | | |
| | (7.095) | (6.946) | | |
| Income Q5 | $18.560^{***}$ | 10.627 | | |
| | (7.047) | (6.977) | | |
| Campaign FEs | No | Yes | No | Yes |
| Donor FEs | No | No | Yes | Yes |
| Observations | 15,488 | 15,488 | 4,040 | 4,040 |
| Adjusted $R^2$ | 0.080 | 0.184 | 0.601 | 0.605 |
| *Note:* | $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ | | | |

### 4.2 Heterogeneity

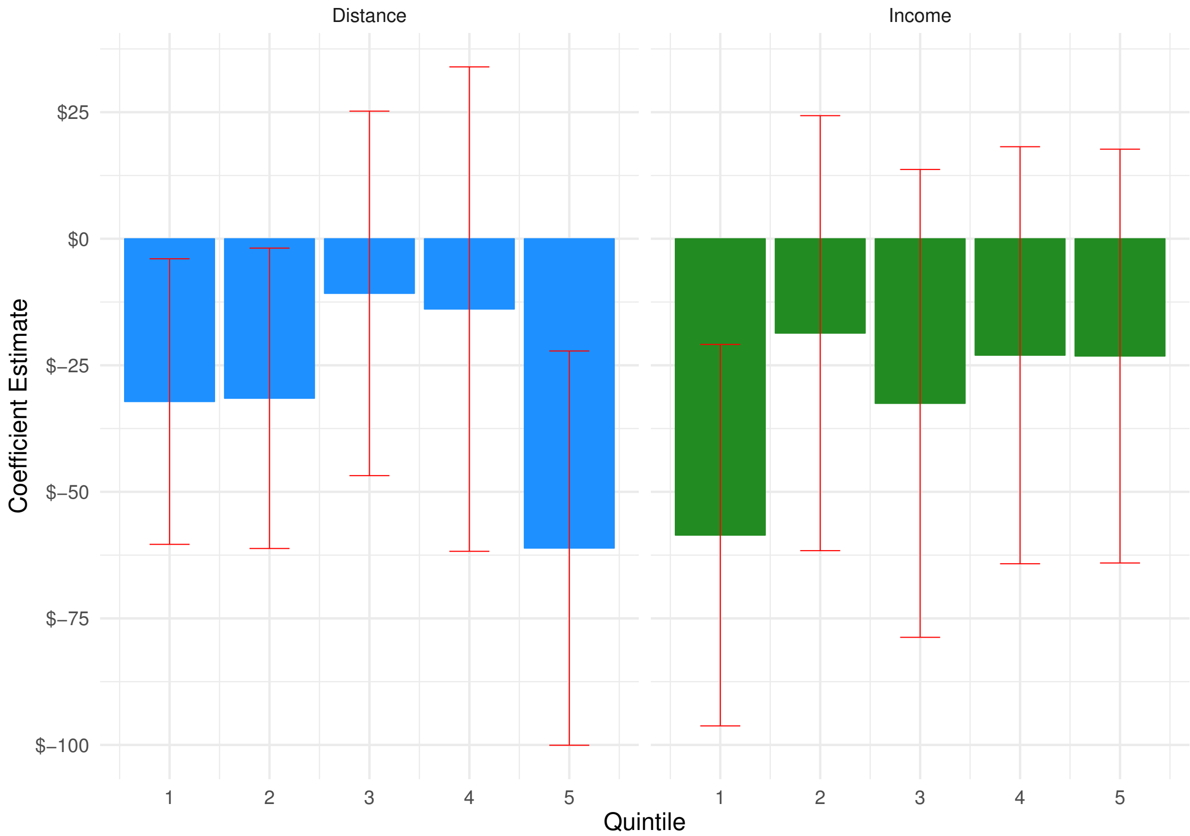
We next examine whether there is heterogeneity in the relationship between ioby tips and donation amounts. To this end, we extend the model presented in column (4) of 2 by interacting $IobyTip_i$ with quintiles of distance and neighborhood income in separate regressions. We focus on heterogeneity for tips because it is the most robust form of crowding out. Figure 2 shows crowding out for all distance quintiles, although only the highest quintile, representing the most distant donors, is statistically significant. Additionally, the coefficient on the fifth quintile is more than double the magnitude of any of the other quintiles in absolute value. This suggests tipping crowds out donors who do not live near the campaign's project, i.e., those who receive less direct benefits from the campaign. Interestingly, this observation would be consistent with predictions of impure altruism. That is, nearby donors will have a marginal willingness to donate that is motivated both by benefits from the project as well as warm glow; on the other hand, distant donors may experience warm glow, but they do not generally get benefits from the projects themselves. Thus, in relative terms, distant donors are more likely to be crowded out by alternative opportunities for charity.

We also see that crowding out from tips is largest in the lowest income neighborhoods. This makes sense if lower income donors face stricter budget constraints and must substitute limited charitable giving funds across causes. One interesting feature of the heterogeneity analysis is that more distant donors are actually wealthier, so distant and low income donors are unlikely an overlapping set.[7]

We further assess heterogeneity by grouping the sample along two dimensions: distance to the campaign and the timing of the donation. For both dimensions we subset the sample by above and below the sample median. For distance, we bifurcate the sample at the median distance from donor to project and for timing we split the sample before and after the midpoint of the campaign. We use our preferred specification presented in column (4) of Table 2, which we replicate in column (1) of Table 4 for reference. For distance, we find that, similar to the results presented in Figure 2, more distant donors are more susceptible to crowding out. This is true for both tips and cumulative donations, although neither difference is statistically different from each other and neither of the coefficients on cumulative donations is statistically significant from zero. We find similar effects when dividing the sample by the timing of the donation: early donors are less susceptible to both types of crowding out relative to later donors. Similar to our analysis of distance, none of the differences between timing groups are statistically significant, but one note is that the cumulative donations coefficient is statistically significantly different from zero at the 10% level in the later-donor sub-sample. The interpretation of the results is similar—closer and earlier donors are more likely to have a strong connection to the project and thus are less susceptible to crowding out of project donations. We acknowledge that the timing analysis may reflect both differences in donor types and timing issues, since earlier donors may have stronger preferences for the project.

[7]The average neighborhood income in each of the five distance quintiles is \$64,064, \$69,277, \$79,690, \$82,935, and \$75,676 respectively.

**Figure 2: Heterogeneity in crowding out from tips by distance and income**




Note: Each panel presents the coefficient estimates for a separate regressions where ioby tips is interacted with quintiles of distance or income. The solid bars represent the coefficient estimates and the error bars are the 95% confidence intervals. All regressions include campaign and donor fixed effects.

**Table 4: Subgroup analysis**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Ioby Tip | −32.019*** | −23.067* | −44.496** | −17.147 | −45.953* |
| | (9.445) | (11.835) | (21.247) | (12.425) | (24.547) |
| Cumulative Donations (%) | −0.310 | 0.669 | −1.932 | −0.566 | −5.445* |
| | (0.644) | (0.973) | (1.576) | (0.730) | (3.061) |
| Campaign FEs | Yes | Yes | Yes | Yes | Yes |
| Donor FEs | Yes | Yes | Yes | Yes | Yes |
| Distance > Median | - | No | Yes | - | - |
| Time > Median | - | - | - | No | Yes |
| Observations | 4,040 | 2,453 | 1,582 | 2,480 | 1,560 |
| Adjusted $R^2$ | 0.584 | 0.654 | 0.312 | 0.518 | 0.589 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

### 4.3 Robustness

We investigate the robustness of our results by examining outliers and different specifications of the standard errors. Since civic crowdfunding typically funds small-scale campaigns and is heavily reliant on small donors, we drop very large campaigns and large donations. Table 5 shows the results when dropping outliers. We define large campaigns as those that collected over \$20,000 and large donations as donations exceeding \$1,000.[8] Column (1) in Table 5 simply replicates our preferred specification in column (4) of Table 2 for comparison. Dropping campaign or donation outliers in isolation reduces both forms of crowding out in similar magnitude. Dropping both types of outliers further reduces crowding out from tips; however, in all specifications crowding out is still negative and statistically significant. Next, Table 6 presents different clustering specifications for the standard errors. Column (1) in Table 6 simply replicates our preferred specification in column (4) of Table 2 for comparison. Column (2) clusters by campaign, column (3) by donor, and column (4) estimates two-way clustered standard errors by campaign and donor (Cameron et al., 2011). Clustering does increase the standard errors but the coefficient on crowding out for tips is still statistically significant at the 5% level. Lastly, in column (5) we drop both types of outliers and cluster the standard errors by campaign and donor, and find that crowding out for tips is significant at the 10% level. Overall, while the magnitude and inference do change by modelling specifications, there is a robust negative relationship between donating to ioby and campaigns.

**Table 5: Robustness to campaign and donation outliers**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Ioby Tip | $-32.019^{***}$ | $-21.810^{**}$ | $-20.553^{***}$ | $-14.563^{***}$ |
| | (9.445) | (10.096) | (4.699) | (5.013) |
| Cumulative Donations (%) | $-0.310$ | $-0.505$ | $-0.168$ | $-0.295$ |
| | (0.644) | (0.674) | (0.319) | (0.334) |
| Campaign FEs | Yes | Yes | Yes | Yes |
| Donor FEs | Yes | Yes | Yes | Yes |
| Campaign > \$20,000 | Yes | No | Yes | No |
| Donation > \$1,000 | Yes | Yes | No | No |
| Observations | 4,040 | 3,658 | 3,984 | 3,608 |
| Adjusted $R^2$ | 0.584 | 0.588 | 0.467 | 0.455 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | | | |

[8] Roughly 0.02% of campaigns are over \$20,000 and 0.01% of donations exceed \$1,000.

**Table 6: Robustness to clustering standard errors**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Ioby Tip | $-32.019^{***}$ | $-32.019^{***}$ | $-32.019^{**}$ | $-32.019^{**}$ | $-14.563^{*}$ |
| | (9.445) | (12.259) | (12.762) | (13.144) | (8.274) |
| Cumulative Donations (%) | $-0.310$ | $-0.310$ | $-0.310$ | $-0.310$ | $-0.295$ |
| | (0.644) | (0.669) | (0.637) | (0.659) | (0.392) |
| Campaign FEs | Yes | Yes | Yes | Yes | Yes |
| Donor FEs | Yes | Yes | Yes | Yes | Yes |
| Campaign > \$20,000 | Yes | Yes | Yes | Yes | No |
| Donation > \$1,000 | Yes | Yes | Yes | Yes | No |
| SE Cluster | None | Campaign | Donor | Donor & Campaign | Donor & Campaign |
| Observations | 4,040 | 4,040 | 4,040 | 4,040 | 3,608 |
| Adjusted $R^2$ | 0.584 | 0.584 | 0.584 | 0.584 | 0.455 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | | | | |

# 5 Conclusion

This paper presents one of the first empirical analyses of civic crowdfunding in the economics literature. We provide evidence on crowding out in two dimensions: (1) between charitable causes and (2) between donors. We find a strong negative relationship between donations to the civic crowdfunding platform and individual campaigns, suggesting crowding out between charitable causes. We find limited evidence of crowding out across donors. Our findings should be interpreted as associations rather than causal relationships, as we rely upon observational data without an experimental intervention or quasi-experimental variation. Even so, this work provides an interesting initial glimpse into different dimensions of crowding out—one of the first such efforts in the field of civic crowdfunding—and sheds light on long-standing questions in public economics and charitable giving.

We conclude with an eye toward future research. Our findings thus far point to several ripe areas for additional inquiry. Foremost, it would be useful to employ an experimental or quasi-experimental design to determine whether the relationships reported herein are causal. Additionally, our analysis nests multiple types of projects, but whether the project type is a factor in crowding out is outside the scope of this research; it would be interesting to examine this possibility in future research. Along these lines, there is a need to better understand the contours and causes of crowding out and crowding in. For example, how do crowding out and crowding in vary over other dimensions of heterogeneity, such as donor demographics and campaign characteristics? Are certain donors or causes more susceptible to crowding out? The answers to these questions will provide useful insights to civic crowdfunding platforms and campaigns, and they will also help inform broader efforts to model and understand charitable giving behavior.

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