Pay-to-play: Political Contributions and Long-term Distortions in Public Procurement*

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Abstract: Political contributions can distort the allocation of public resources, yet the mechanisms that allow favoritism toward campaign donors to persist remain poorly understood. Using administrative data linking campaign contributions in mayoral elections to the universe of procurement contracts in Colombia from 2012 to 2025, we show that donors not only obtain more valuable discretionary contracts and experience more and larger cost overruns, but also retain these advantages, relative to non-donors, even long after their political connections disappear and despite of strict regulations. To identify the frictions that sustain these persistent distortions, we implement a nationwide randomized controlled trial in partnership with the Inspector General's Office, investigative journalists, and two civil society organizations. The intervention provides recently elected mayors with information on procurement rules related to donations and equips their different principals with monitoring capacity. This design allows us to identify the source of *informational asymmetries* that limit principals' ability to detect and discipline favoritism. Cost-effective deterrence emerges only when *both* legal principals and mayors receive *actionable information* that reveals the identity and recent contracting activity of donors. Leveraging this variation and the administrative data, we estimate a dynamic structural model that *jointly* incorporates the two key selection margins, donation and entry, through which forward looking individuals and firms choose how to behave over electoral cycles. The model estimates the sunk and operational costs that sustain favoritism and the rest of the reduced form patters, while reconciling the surprisingly low scale of political giving relative to its apparent large returns. Counterfactual policy exercises show how typical regulatory interventions can reduce welfare and why they rarely eliminate the distortions created by campaign contributions.

Keywords: Public Procurement, Campaign Contributions, Donor Selection

JEL codes: D72, H57, P00

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1 Introduction

Money plays a central role in politics, serving both as a driver of democratic competition and as a source of political and economic distortions (IDEA, 2014). Political contributions, for example, can influence electoral outcomes, regulation, and the allocation of public resources (Ansolabehere, De Figueiredo and Snyder Jr, 2003; Colonnelli, Prem and Teso, 2020; Brugués, Brugués and Giambra, 2024). Yet, far less is known about the particular frictions that sustain these distortions, the types of policies that can mitigate them, and the welfare consequences that follow (Bombardini and Trebbi, 2020). Understanding these elements from the perspective of politicians and private actors is essential for determining how economic incentives translate into political influence and how political finance regulations and oversight could ultimately discipline this process.

In this paper, we take a step in this direction by asking which informational asymmetries and hidden costs sustain the continued influence of money on political favoritism, and what, if anything, policymakers and civil society can do in response. We focus specifically on the informational asymmetries in *local governments* that allow politicians to maintain preferential treatment in *public procurement* for *campaign donors*. We then study how these frictions interact in *general equilibrium* to shape the decisions of individuals and firms to donate and to participate in procurement markets, an activity that accounts for nearly one quarter of all government spending worldwide (OECD, 2019; World Bank, 2020).

Progress on these questions has been constrained by three fundamental challenges. The first is the lack of granular data linking local political contributions to public contracts, which prevented researchers, until very recently, from tracing how private money translates into preferential treatment within local governments. The second is a predominant focus on politicians, big donors, individuals and firms, in isolation, which have obscured how information, hidden costs, and strategic responses on all sides of the market *jointly* sustain these distortions. The third is limited attention to the distinct selection margins that shape individuals' and firms' behavior over the electoral cycle and in public procurement, including entry, exit, and the timing of donations (Bombardini and Trebbi, 2020). This omission has constrained the ability to disentangle the existing informational gaps from other documented mechanisms in the literature, and to evaluate the welfare implications of the policies that could mitigate them.

We address these challenges by developing an approach that integrates three complementary empirical strategies. First, using newly linked administrative data with national identification numbers, we conduct reduced-form analyses comparing procurement outcomes for donors and non-donors across multiple electoral cycles. This strategy allows us to document the long-term returns and inefficiencies associated with the preferential treatment that local politicians extend to donors. Second, we design and implement a nationwide randomized controlled trial that targets three informational asymmetries that may sustain donors' persistent advantages: i) limited knowledge of regulations governing contracting

with donors, ii) limited information and monitoring capacity by specific oversight principals, and iii) limited scope for deniability among non-compliant donors. Finally, using the variation generated by the first two strategies, we estimate a structural model that incorporates politicians' allocation incentives together with private agents' forward-looking decisions over electoral cycles. This framework allows us to quantify the hidden sunk and operational costs faced by individuals and firms, identify the incentives shaping participation in public procurement markets, and evaluate both new and existing policy proposals intended to reduce the distortions that political contributions create in local governments.

We focus our empirical analysis on the municipal governments of Colombia, which provide an unusually rich environment for examining how the distortions of political contributions operate in practice. Three features make Colombia especially suitable for this analysis. First, mayors possess broad discretion over procurement. They are responsible for all municipal spending and sign all contracts. Most procurement procedures bypass open tender because rules permit extensive direct contracting and minimum value procedures, which are common for the small infrastructure, operational, and administrative tasks that dominate local procurement. Although regulations limit donor participation under specific conditions, enforcement is weak, which may reflect either uneven monitoring capacities or deeper informational constraints that limit oversight of favoritism. Second, local elections create concentrated links between candidates and contractors. Mayoral campaigns depend heavily on private contributions because public funds cover little of their cost, and population based limits make even modest donations influential. Finally, political campaigns at the municipal level remains highly personalized, which further sharpens the incentives for candidates and contractors to form close relationships, and leaves procurement decisions especially vulnerable to the influence of campaign finance.

Our empirical analysis proceeds in three steps. In the first part of the paper, we examine how political campaign contributions shape access to public procurement highlighting the systematic differences between those who participate in campaign finance and those who do not during the 2015 and 2019 mayoral elections. We start this analysis by documenting new stylized facts about the differences between donors and non-donors. We show that contributors to mayoral elections tend to be, on average, less experienced, more financially vulnerable, and more connected to bureaucrats in the public sector. They are also more reliant on discretionary contracting and bunch disproportionately around contracting limits when compared to non-donors. They remain in the procurement system longer and exit at a lower rate than non-donors once they get their first contract. However, once elections take place, individuals and firms that donated gain notable advantages in public procurement. Using a stacked difference-in-differences framework that exploits within-individual and within-firm variation in donation status, we find that campaign contributors become 28% more likely to win contracts and to secure 17% more valuable ones. Yet this occurs at the expense of efficiency in contract execution. Donors' contracts tend to report 5% more frequent and 9.2% more expensive overruns. Crucially, we also show that these distortions persist through political turnovers. Even though repeated

donations across multiple elections are rare (only 3.7% of individuals and firms do it), donors continue to receive contracts well beyond the election in which they contributed, and they face similarly large efficiency costs for as long as eight years.[1]

In the second part of the paper, we examine the systematic forces that sustain these long-term distortions. Building on our results and the qualitative evidence gathered in prior fieldwork, we ask what specific information asymmetries allow politicians to favor their donors. To study these asymmetries, we partner with the Colombia Inspector General's Office, investigative journalists, and two civil society organizations, the Instituto Anticorrupción and the Open Contracting Partnership, to implement a nationwide randomized control trial designed to identify and weaken the informational gaps that support these distortions. The intervention, conducted after the 2023 mayoral elections, tests four hypotheses. The first is that favoritism persists because mayors lack adequate information about the regulations governing contracting with donors. The second is that even when such information is available, oversight bodies face limited monitoring capacity that depends on their identity and legal authority. The third is that even when information and monitoring capacity exist, favoritism may continue if mayors believe oversight principals will find it too costly to use their capacity effectively to detect donor-related irregularities. The fourth is that even when information and capacity are accessible and inexpensive to deploy, favoritism may endure if mayors cannot credibly signal to donors that they are being effectively monitored at the moment a favor is requested, which undermines their ability to refuse such requests.

To evaluate these channels, we focus on municipalities that report at least one campaign donor during the 2023 campaign and randomly assign their mayors to different treatment arms six months after they took office. Within this sample, mayors are first divided into a control group and a "letter group." The control group includes a pure follow up arm, which receives no communication, and a placebo-letter arm, which receives a neutral message unrelated to donors or procurement. The remaining mayors receive letters reminding them of the regulations that restrict contracting with campaign donors. For these mayors, we vary two dimensions of the letters. The first dimension changes the identity of the oversight actor: the letter is either not copied to anyone, copied to investigative journalists, or copied to the Inspector General's Office. The second dimension changes the information attached to the letter. Some mayors receive no list of donors, while others receive either a full list of all donors in the municipality and their recent procurement histories, or a partial list created by randomly dropping one donor from the full list. These variations change who is perceived to be monitoring and how visible donor–contract links are, allowing us to identify which informational asymmetries sustain preferential

[1] In contrast to prior work, donors to both the winner and the runner-up gain relative to non-donors. To benchmark these results with existing results in the literature, we replicate the close-election design used in Colonnelli, Prem and Teso (2020). This exercise confirms that donors to the winner earn higher returns in close elections, although we cannot rule out that the returns to donors to the winner and to the runner-up differ statistically from each other relative to non-donors. Since both groups benefit, our findings reveal an additional margin of distortion that operates even outside very politically competitive municipalities.

treatment and to quantify how relaxing them affects procurement outcomes.

We find that mayors reduce favoritism only when the letter references the Inspector General's Office and includes the donor lists. This pattern indicates that deterrence requires a threat of punishment that is credible, costly, and paired with information that lowers principals' costs of detecting irregularities. Donors in treated municipalities are 30% less likely to receive contracts and obtain contracts that are 4.3% lower in value compared to donors in control areas. The impact is strongest for donors to the incumbent mayor, who are precisely those most exposed to scrutiny under credible oversight. The intervention also improves efficiency, since treated donors face 6% lower cost overruns and receive discretionary contracts that are 5% lower in value. By contrast, we find no effects for donors from previous electoral cycles or for municipalities assigned to the other treatment arms.

Taken together, these results show that distortions generated by informational frictions must be addressed early to prevent the long-term entrenchment of specific interest groups. They also suggest that lighter informational interventions, which are comparatively inexpensive, scalable, and easily repeated, can generate deterrence effects that approach those of audits. Audits rely primarily on the fear of being caught, which can deter misconduct but may also create unintended consequences for compliant contractors (Gerardino, Litschig and Pomeranz, 2024) and may not resolve the underlying informational asymmetries that allow favoritism to persist. In contrast, interventions that directly improve information flow can target the core problem more strategically and at far lower cost.

In the third part of the paper, we bring together the descriptive patterns and the experimental responses by developing a dynamic discrete choice model that captures how these distortions operate in equilibrium. The experimental evidence shows that credible oversight curtails favoritism in the moment, yet it also illustrates that donor advantages endure as long as contributing remains a profitable strategy. This insight guides the model's design. Firms decide whether to enter or exit procurement markets and whether to donate during election years, taking into account that donations require a sunk cost that either provides differential production costs relative to non donors or further weakens competitive pressure. These choices influence firms' long run presence in procurement and shape their transitions across donor and non donor states, even in the presence of idiosyncratic shocks. The model follows how these dynamics compound over successive electoral cycles and offers a structured way to connect the local effects of oversight to the broader incentives that sustain the donor advantage.

Using this framework, we estimate mayors' contract demand from the exogenous variation generated by the RCT, recover implied marginal production costs through competitive Cournot first order conditions, and embed per period profits in a dynamic discrete choice environment solved in a type symmetric equilibrium. We solve the model by backward induction and estimate it via maximum likelihood, which allows the data to identify the full set of structural parameters instead of relying on calibration or moment matching.

Our structural estimates show that the sunk cost of donating exceeds the value of the average campaign contribution observed in the data by 84%, indicating that firms face substantial hidden

costs. These are not arbitrary but systematically correlate with local institutional characteristics. Counterintuitively, donors also exhibit smaller operational benefits than non-donors, which we interpret as evidence that politically connected firms may operate under looser budget constraints or weaker competitive pressure that limits their efficiency gains. Using the estimated parameters, we compute the implicit rate of return on these investments as the net present value of public procurement for donor firms. Once hidden costs, fringe benefits, and operational expenses are taken into account, the median net returns are roughly 50% lower than the reduced-form evidence alone would suggest. This provides a micro-founded explanation for why political donations remain limited in scale. These findings echo the classic Tullock puzzle (Tullock, 1972; Ansolabehere, De Figueiredo and Snyder Jr, 2003), in which spending on rent-seeking remains small despite the supposedly large returns associated with political favoritism. While the literature interprets this gap (101% vs 47%) as evidence of expenditure constraints, collective-action frictions, or alternative influence channels that prevent full dissipation of rents through political competition, we show that even before invoking these mechanisms, returns are not as large as naive estimations based solely on administrative data would imply.

More importantly, we evaluate the welfare implications of several counterfactual policies frequently proposed to reduce the distortions of campaign contributions, in general, and in public procurement, in particular. We examine five scenarios: the expressive-value interpretation of donations, in which contributions provide intrinsic utility but no quid pro quo (i.e., do not generate changes in marginal costs of production); a complete ban on donations; perfect enforcement of the rule that donors cannot receive contracts; cooling-off periods between contributing and contract eligibility; and increases in the threshold for discretionary contracting relative to open tender. We find that none of these alternatives are welfare enhancing relative to the status quo. While they deter donors from competing directly and favoritism from happening, the general equilibrium effects induced by the earlier exit of high-performing donors generate overall welfare losses.

This paper contributes to several strands of the economics and political science literature. First, we speak to the literature on accountability and oversight in public sector organizations (Duggan and Martinelli, 2017; Acharya, Lipnowski and Ramos, 2024; Moore, Pande and Schaner, 2025). Prior work have shown that randomized audits raise the probability of detection and thereby reduce corruption (Olken, 2007; Ferraz and Finan, 2008; Duggan and Martinelli, 2017; Zamboni and Litschig, 2018; Avis, Ferraz and Finan, 2018; Colonnelli and Prem, 2022). However, audits often require considerable administrative resources, skilled personnel, repeated verification processes, and credible sanctioning capacity, which limits their scalability and cost-effectiveness (Cuneo, Leder-Luis and Vannutelli, 2023). They may also discourage competitive procedures in procurement contexts, inadvertently increasing discretion (Gerardino, Litschig and Pomeranz, 2024). This is particularly important to emphasize because in many countries, formal procurement laws differ sharply from actual practice due to weak enforcement and limited capacity (Bosio et al., 2020). In contrast, our intervention uses a low-cost mechanism —merging donor and contracting databases, sending targeted letters/emails, and activating

monitoring capacity— to create a credible oversight threat.

To our knowledge, we provide the first nationwide randomized controlled trial in which an inexpensive, scalable information-revelation strategy directly tests and tackles the informational asymmetries that sustain political favoritism in procurement. We isolate the specific form of asymmetry that enables favoritism, implement a cost-effective intervention that significantly mitigates it, and link it to high-frequency administrative contracting data to evaluate its effect. We contribute with new evidence on how information environments shape political accountability even in settings where formal oversight institutions and nominal monitoring capacity already exist and where audits are not readily available.

Second, we contribute to the literature on money in politics. Existing work examines a variety of regulatory approaches intended to limit the influence of political contributions (Baltrunaite, 2020; Gulzar, Rueda and Ruiz, 2022; Avis et al., 2022; Aparicio and Avenancio-León, 2022), yet these policies often neglect the joint incentives of politicians and donors. Our framework brings these incentives together. On the political side, the randomized intervention targets mayors and shows that increasing the credibility of oversight through the disclosure of donor links reduces their willingness to allocate contracts preferentially. On the donor side, the structural model reveals sizable hidden costs of contributing that do not appear in administrative campaign records and that meaningfully shape participation decisions. This perspective aligns with recent evidence that procurement markets often operate in equilibria with limited entry and persistent advantages for established or politically connected firms due to informational frictions (Kang and Miller, 2022).

We also broaden the empirical evidence on political influence. Much of the literature focuses on lobbying, contributions, and regulatory access in advanced economies,[2] while research in developing settings typically examines whether donors supported winning or losing candidates (Boas, Hidalgo and Richardson, 2014; Titl and Geys, 2019; Ruiz, 2021). Using linked administrative data spanning three electoral cycles, we document a systematic and persistent relationship between campaign contributions and procurement outcomes. Donors obtain substantial advantages irrespective of which candidate they supported, and these advantages persist across political turnover. This pattern indicates that contributions operate as long-horizon investments rather than short-run bets on electoral success.

These findings relate directly to a variant of the classic Tullock puzzle (Tullock, 1972) and provide a new explanation for the relatively small volume of political contributions even in low and middle income countries (Ansolabehere, De Figueiredo and Snyder Jr, 2003). By estimating the sunk and operational costs associated with donating and entering procurement markets, the structural model recovers implicit, model-based rates of return to political giving. Incorporating these costs reduces net returns considerably relative to what procurement advantages alone would imply. This mechanism

[2]For instance Bombardini and Trebbi (2011); Aggarwal, Meschke and Wang (2012); Bertrand, Bombardini and Trebbi (2014); Kalla and Broockman (2016); Powell and Grimmer (2016); Le and Yalcin (2018); Huneeus and Kim (2018); Kim, Stuckatz and Wolters (2020); Bombardini and Trebbi (2020); Fowler, Garro and Spenkuch (2020); Teso (2023); Hirsch et al. (2023); Grotteria (2024).

offers a micro-founded rationale for the limited scale of political contributions observed in our setting and clarifies how economic incentives influence the formation of political connections.

Third, this paper contributes to the literature on distortions and misallocation of public resources arising from political connections.[3] We develop a dynamic structural model that incorporates political connections through firms' donation decisions and their entry or exit from the public procurement market. The model captures the central selection margins of donation and entry and embeds forward-looking behavior in a general equilibrium environment with economic competition. Our findings that donor advantages persist over long horizons are consistent with evidence that procurement markets can generate equilibrium patterns of limited competition due to informational and institutional frictions (Kang, 2016; Kang and Miller, 2022). A key feature is that we estimate the model via maximum likelihood rather than relying solely on calibration or method of moments. This approach allows us to recover the sunk and operational costs that shape firms' behavior across electoral cycles and to assess the empirical validity of the model's core mechanisms. The framework provides a tractable, estimable, and exportable tool for studying political donations in local elections and competition in discretionary procurement markets, and it supports counterfactual analysis of policies designed to reduce distortions generated by political connections.

The rest of the paper is organized as as follows. Section 2 describes the mayoral elections in Colombia and details on public procurement procedures. Section 3 describes the administrative procurement records and mandatory reports of political donations. Section 4 describes the relationship between donations and public procurement, and examines the returns from donating to political campaigns. Section 5 presents the nationwide randomized controlled trial. Section 6 presents the structural model and the policy counterfactual. Finally, Section 7 concludes.

2 Institutional Background

Electoral Organization and Political Financing Local elections take place every four years in roughly 1,120 municipalities. Political campaigns run from June to October in the last year of the incumbent's term, voting occurs in October, and the winning candidate takes office in January. Mayors are elected by plurality rule and are term limited, although they can run for other positions or run for mayor again after a government cycle, while runner-up candidates typically secure a seat in the municipal council. The process is organized by the National Electoral Comission, who also defines campaign finance regulations and oversees political parties.

Candidates are only allowed to use resources for political campaigns during the electoral period. The main funding sources are close relatives' and private contributions (MOE, 2019), which they can spend subject to limits based on municipal population. Similarly, private contributions cannot

[3] See for instance Auriol, Straub and Flochel (2016); Mironov and Zhuravskaya (2016); Schoenherr (2019); Baranek and Titl (2020); Colonnelli, Prem and Teso (2020); Baltrunaite et al. (2021); Weaver (2021); Szucs (2023); Dahis, Ricca and Scot (2024); Brugués, Brugués and Giambra (2024).

exceed 10% of such spending limit.[4] These rules aim to limit the influence of money in politics (IDEA, 2014; Gulzar, Rueda and Ruiz, 2022; Avis et al., 2022). In addition, donations must be reported to the authorities, certified by an accountant and approved by the candidate's party. The reports must include the name of the donor, the amount donated, and the identification number. Non-compliance can result in destitution from office, fines, and jail-time.

Municipal Government Financing and Public Procurement Mayors are the highest municipal authorities and are responsible for providing public goods and services. Municipal budget consist on national transfer and local taxes. Transfers are formula-determined and must be used for specific purposes, such as education or health. On the other hand, locally collected income can be used at the full discretion of the municipal government (Carreri and Martinez, 2022).

Most municipal spending occurs through public procurement, which represents about 13.3% of the national GDP and a third of government spending, underscoring its importance in economic activity (OECD, 2020). The National Agency for Public Procurement regulates contracting procedures and provides support to local governments, but procurement is decentralized, so municipalities independently determine what goods and services to procure.

Procurement procedures vary by the degree of competition needed to select a contractor. Large contracts require a public tender, in which various firms present proposals, and the best one is chosen. Contracts valued below a threshold follow a "minimum value" procedure, for which only one proposal is required so competition can be avoided in exchange for a faster assignment. Finally, there are fully discretionary contracts –direct procurement–, which are mainly used to provide personnel for public offices (see Appendix A.1 for details). Mayors enjoy significant discretion in the assignment of small-value and bureaucratic tasks contracts.[5]

Political Campaign Donors and Participation in Public Procurement While it is not illegal for political campaign donors to receive public contracts, their participation in procurement is regulated. Donors cannot receive public contracts if the total donated amount exceeded 2% of the candidate's spending limit. The ban applies to firms' representatives and board members. Donors are also forbid to receive public contracts if they face disciplinary investigations or corruption sanctions. In addition, individuals cannot donate if more than half of their income comes from public contracts, so if a contractor donates to a political campaign, can be subject to disciplinary investigation and would not be allowed to receive further contracts.

Despite existing regulations, political campaign donors are frequently involved in corruption cases related to illegal contract allocation or misuse of resources (see Figure A1). The most common

[4]There are no limits on family contributions as long as they do not exceed the spending limit. Candidates can also obtain funding from the government in the form of refunds or from bank loans.

[5]We use these two categories, namely 'minimum value' and 'direct' contracts, in our analysis of mayoral discretionary contract allocation below.

accusation against political candidates and their donors include kickbacks in exchange for donations, approval of cost overruns, and bypassing competitive procedures to favor specific firms (MOE, 2018). It is also common for politicians to allocate contracts to donors who exceeded donations thresholds (MOE, 2018; Transparency International Colombia, 2024), who are investigated or have been sanctioned for corruption (Transparency International Colombia, 2019) or have been previously contractors supporting a political campaigns.[6]

Public Procurement Oversight Disciplinary investigations involving public officials and contractors are the responsibility of the Office of the Inspector General, which can also prosecute those found responsible for corruption. As such, the agency must ensure compliance with procurement regulations, but in practice it cannot oversee the full scope of local procurement. According to MOE (2018), the Inspector General has weak capacity to audit contracting procedures, and to use the available data to detect irregularities, which further increases corruption risks in procurement since municipalities do not use the donation reports to verify conflicts of interest.

Civil society also plays an oversight role through social control. National-level media regularly cover corruption cases and pressure authorities to sanction officials. Coverage by these organizations provides an additional independent identification of potentially corrupt practices in contract allocation. Such scandals commonly emerge around elections, when mayors are receiving donations, or after elections, when donors are awarded public contracts. Still, anecdotal evidence suggests that limited monitoring and enforcement capacity of the Office of the Inspector General makes it difficult for civil society efforts to translate into punishment or discipline in procurement.

3 Data and Descriptive Patterns

3.1 Data Sources

Donations to Political Campaigns We collect donations data for the mayoral elections held in 2015, 2019, and 2023 from the web platform *Cuentas Claras* developed by Transparency International Colombia and the National Electoral Commission.[7] Since 2013, all candidates have been required to upload their financing reports to the platform, even if they received no contributions. The reports include the names and national identification numbers of donors (individuals and firms), the recipient candidates, and the value of the donation.

Reporting compliance is high: according to the National Electoral Commission, 92% of candidates submit their financing reports. However, alongside official reports, funds might be received "under the table". These issue has been flagged in national-level elections, where candidates have been investigated

[6] A highlighted case from the mayoral elections in 2023 consists of a mayoral candidate in Medellin, the second largest municipality in Colombia, who received close to 50% of its donations from public contractors.

[7] See https://www.cnecuentasclaras.gov.co/, https://transparenciacolombia.org.co/

for omitting donations and exceeding spending thresholds.[8] Reports of undeclared donations in local elections are less frequent. Yet, in our analysis below, non-reported donors would be classified as non-donors. As a result, any effects we identify can be interpreted as a lower bound.

Public Procurement We compile procurement data from the "Electronic System for Public Procurement" (SECOP, for its Spanish acronym) managed by the National Agency for Public Procurement. The system collects and publishes comprehensive information on all public contracts, including value, duration, description, contractor name, and national identification number. Importantly, the national identification number uniquely identifies each individual and firm across any national administrative dataset, allowing us to link contractors to political donors following Ruiz (2021); Gulzar, Rueda and Ruiz (2022); Gulzar, Purroy and Ruiz (2022) (see Figure A2).

Panel Dataset of Donors and Contractors The high frequency of the data allows us to use different time aggregations. We use individual-by-half-year data for studying the returns to donating (Section 4.2), and individual-by-month data for the randomized controlled trial (Section 5). In each case, we create a balanced panel where firms with no contracts in a period are coded as zero. The few donors appearing in multiple elections are assigned to the first one (see Figure A3).

These data allow us to identify donors who receive contracts and those who do not, but for non-donors we only observe contractors. To estimate the effect of donating we must also include non-donor, non-contractors. Otherwise, we would be comparing successful and non-successful donors against only successful non-donors, mechanically underestimating the effect of donations.

To overcome this issue, we use the 2018 National Census to recover the population of non-donor, non-contractors. First, we count the number of households in each municipality and assume that each includes at least one person who can donate and receive a public contract. The assumption is plausible as all citizens above the legal age are allowed to donate (if they have no disciplinary sanctions), and can participate in public procurement (if they meet contract requirements). Second, we subtract the number of contractors and donors from the number of eligible individuals. The resulting number of non-donors, non-contractors are incorporated into the balanced panels. We present robustness to alternative samples in Section 4.2.

3.2 Descriptive Patterns

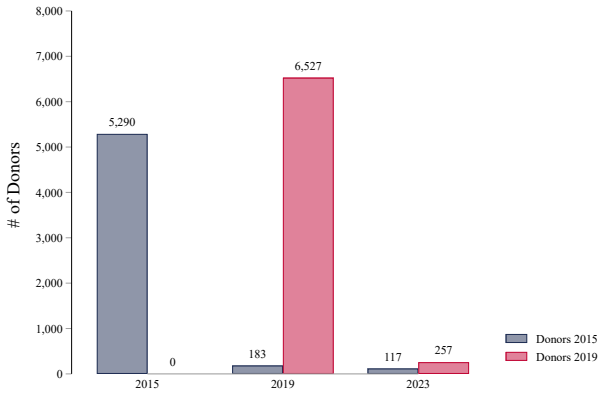
Donations to Political Campaigns We observe close to 20,000 unique donors across the three elections. On average, each donor contributes to one candidate and does so in only one election (1.1% donate in all three). Panel (a) of Figure 1 shows that fewer only 3.7% of donors in 2015 (blue) and 2019 (red) donated again in the next electoral period. Panel (b) displays the distribution of donation

[8] As an example, national media reported that the winning candidate in the 2024 presidential elections omitted donations coming from contractors and business owners, resulting in exceeded spending limits.

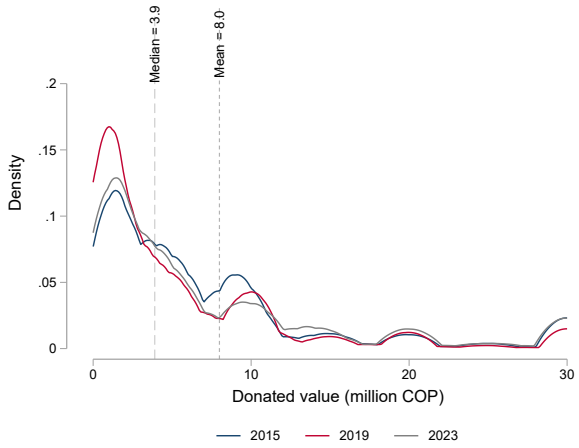
amounts. The average is about 8 million COP ($2,000 USD) with the median of 4 million COP ($1,000 USD),[9] roughly eight and four times the minimum legal monthly wage. Yet, only 16% of them ever receive a contract (see Table A1). Such large contributions, low overlap across elections, and low probability of receiving a contract suggest that donating is a costly and strategic decision rather than a routine campaign expense.

Figure 1: Donors Characteristics

(a) Donor rarely overlap across elections



(b) Distribution of donated values



Note: Panel (a) reports the number of donors for the 2015 and 2019 electoral cycles, separating between those that initially donated in the 2015 elections (blue) or 2019 elections (red). Panel (b) reports the distribution of donated values by individual or firms for each electoral cycles in our data. Donated values are winsorized to the 95^{th} percentile for visualization. Reported mean and median consider the full distribution.

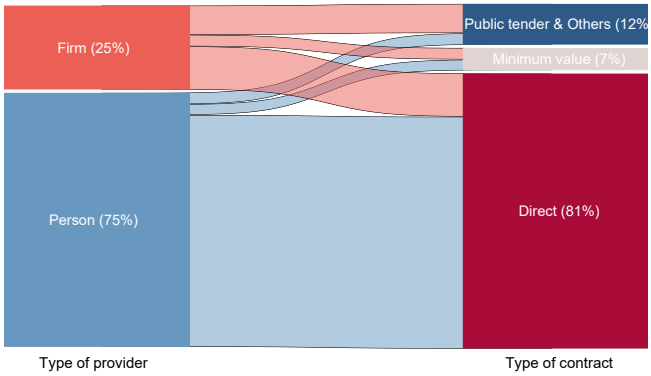
Public Procurement Between 2012 and 2024, local governments signed about 7 million contracts. Panel (a) in Figure 2 shows their distribution by type of procurement procedure. Only 25% of the contracts are assigned to firms, and most of them are allocated through direct procurement. Competitive procedures account for 20% of the contracts, with minimum value being about one-third of them. Panel (b) describes the monthly distribution of contract. Most of them are signed in January and February, coinciding with the start of the fiscal year. A second peak appears in June, consistent with the average contract duration being four months, indicating that new contracts need to be issued. Despite these peaks, contracts are signed every month. The figure highlights that public procurement relies heavily on discretionary contract allocation throughout the year.

Panel A in Table 1 reports statistics for all public contracts in our data. The average contract value is 21 million COP, roughly 20 times the minimum monthly wage. The median is 8.4 million COP, indicating a few high-value contracts skew the distribution. Contract duration averages 4 months, with a median of 3 months. Contracts are also frequently renegotiated: 10% report cost overruns. Panel

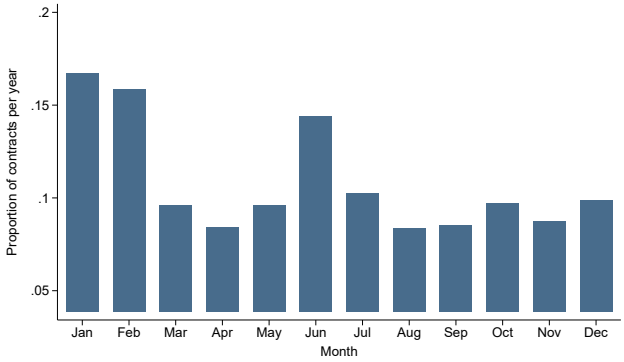
[9]Using the average exchange rate in 2024, approximately 4,000 COP per dollar.

Figure 2: Public Procurement System Features

(a) Distribution of contractors and types of contract



(b) Distribution of contract assignment date



Note: This figure describes two features of the procurement system in Colombia. Panel (a) plots the distribution of contracts assigned by type of contractor (individual or firm) and type of procurement (direct, minimum value, public tenders and others). Panel (b) report the time distribution of the contracts assigned by month of signature.

B and C describes contracts awarded to non-donors and donors, respectively. Contracts awarded to donors have higher average and median values, with a similar standard deviation. Yet, average contract duration differ in less than a month between donors and non-donors. Thus, differences in contract duration cannot fully explain larger contracts being allocated to donors.

Table 1: Summary Statistics of Public Contracts

Panel A: All contracts	Mean	Median	Std. Dev.	Max.	Obs.
Contract value (million COP)	21.212	8.462	61	1,010	6,829,966
Contract overruns (%)	0.098	0.000	0	1	6,829,966
Duration (months)	3.994	3.000	4	205	6,829,966
Panel B: Non-donors contracts	Mean	Median	Std. Dev.	Max.	Obs.
Contract value (million COP)	21.107	8.456	61	1,010	6,730,909
Contract overruns (%)	0.099	0.000	0	1	6,730,909
Duration (months)	4.003	3.000	4	205	6,730,909
Panel C: Donor contracts	Mean	Median	Std. Dev.	Max.	Obs.
Contract value (million COP)	28.321	8.920	79	1,009	99,057
Contract overruns (%)	0.057	0.000	0	1	99,057
Duration (months)	3.372	2.000	5	180	99,057

Notes: This table shows the summary statistics for the public contracts signed between Jan/2012-December/2024 separating between All contracts (Panel A), contracts to non-donors (Panel B) and contracts awarded to ever donors (Panel C). Each observation is a contract.

Public Procurement Dynamics by Donation Status Figure 3 describes the market structure. Panel (a) shows the share of contractors who are donors over time. Only a small share of contractors are

donors, despite the descriptive returns from donating being 3.5 times the observed cost of donating.[10] The pattern is consistent with the Tullock Puzzle (Tullock, 1972), in which few firms contribute to politicians despite the potential large returns (Ansolabehere, De Figueiredo and Snyder Jr, 2003; Kang and Miller, 2022). This observation suggests that barriers to entry may limit participation in procurement for firms seeking preferential access through political contributions. Panel (a) also shows that donors peaks around election years, indicating that donation behavior is cyclical, with firms adjusting their status around political cycles.

Panel (b) shows contractor entry and exit over time, highlighting substantial turnover, which increases significantly in the years following elections. This suggests that participation in public procurement is dynamic and driven by political conditions. Panel (c) complements this by showing that donors exhibit lower exit rates, indicating that donors can retain preferential access. Finally, Panel (d) tracks the total number of contracts assigned over time, revealing a key pattern: donor firms maintain a disproportionately large share of contracts relative to their representation in the contractor pool. We revisit this patterns in Section 6 to introduce the structural model.

4 Political Donations and Public Contract Allocation

In this section, we examine the relationship between political campaign contributions and public procurement. Estimating the impact of donating poses a key empirical challenge: firms that choose to donate are unlikely to be randomly drawn from the pool of potential contractors. We first analyze which firm characteristics predict donating and how contractors decide to enter procurement. Understanding these patterns helps characterize pre-existing differences between firms and the strategic incentives that drives entry into public procurement. We then estimate the returns to donating and assess the extent to which political contributions distort the allocation of public resources, focusing on donors' advantages, efficiency losses, and the persistence of effects.

4.1 Patterns of Selection into Donation and Public Procurement

Characteristics Predicting Donation We explore the characteristics predicting who self-selects into donating using financial firm characteristics from ORBIS (van Dijk, 2024), and individual characteristics using administrative data built by Riaño (2021).[11] We match the data sources using the national identification number and aggregate the matched units at the individual $\times$ election level. We estimate a equation $D_{i,s} = \delta_s + \mathbf{X}_{i,s} + \varepsilon_{i,s}$, where $D_{i,s}$ is equal to one if the contractor i is a donor for election s,

[10] Measured as the ratio between the average contract value for donors in Table 1 and the average donated value from Figure 1: $\frac{28.321}{7.994} = 3.542$

[11] ORBIS contains financial information for private companies worldwide, while Riaño (2021) consist on the career paths of public officials in Colombia. Using the national identification number we match 18.5% of the firms and 34% of the individuals in our dataset (contractors and donors). We do not recover all firms as some are relatively small, so are not observed in ORBIS. Similarly, Riaño (2021) covers all public servants between 2011 and 2017, so it does not include our full timeline, and only consider contractors performing administrative tasks within a public office. The main results in the next sections also hold for the sample used for the analyses in this section.

Figure 3: Public Procurement Market Dynamics for Donor and Non-donors



Note: The panels in the figure describe the market structure of public procurement contracts. Panel (a) shows the proportion of contractors that are donors for each year. Panel (b) describes the number of contractors entering and exiting the procurement system –in terms of receiving or not a contract– by year. Panel (c) describes the average share of exit rate of donors and non-donors. Panel (d) show the time trends of the total number of contracts assigned to donors and non-donors by year. Left axis correspond to non-donors, right axis to donors.

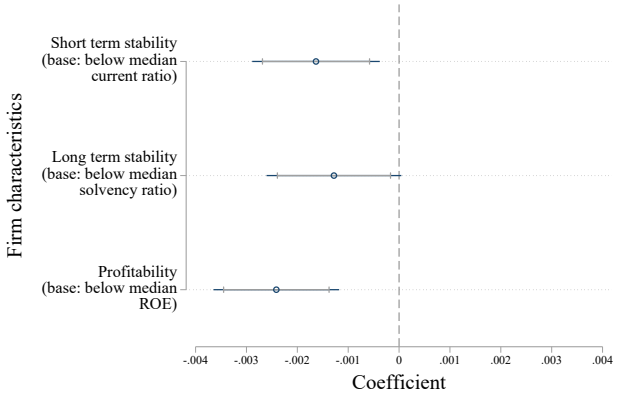
and zero otherwise. $\mathbf{X}_{i,s}$ is a vector of pre-election characteristics, so its coefficients show how each covariate predicts the donation status. γ_s are fixed effects that ensure comparisons within electoral races. Standard errors are clustered at the individual level.

Panel (a) in Figure 4 use financial performance as predictor for firms donation, and Panel(b) uses public service characteristics for individuals donation. Firms donation is predicted by having worse performance: i) lower short-term capacity, ii) lower long-term stability, and iii) a lower profitability. Individual donations are predicted by having a family member in the public sector, suggesting higher probability of nepotism. Donors are also less likely to have had any work experience despite being more likely to have at least an undergraduate degree. The results suggest that selection into donation is predicted by financially weaker firms and connected individuals with little work experience.

Donors Advantage in Discretionary Public Procurement We explore the extent to which donors select into procurement by analyzing bunching behavior (Coviello, Guglielmo and Spagnolo, 2018;

Figure 4: Selection Margins

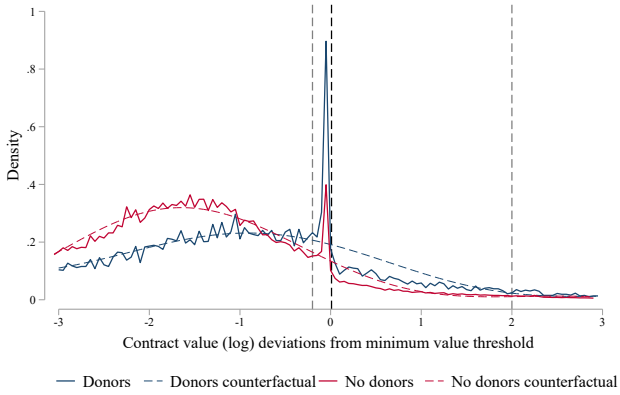
(a) Firms characteristics predicting donation



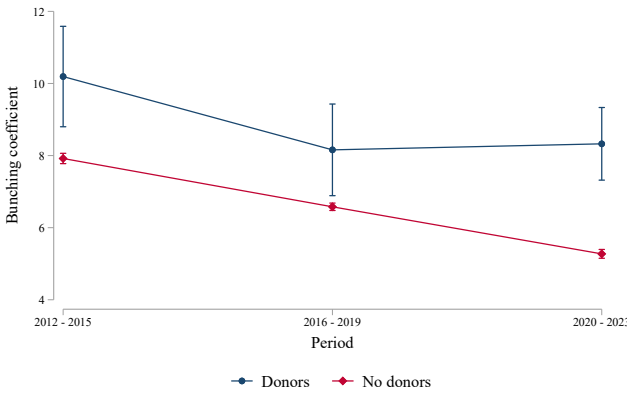
(b) Individual characteristics predicting donation



(c) Contract bunching around discretionary threshold



(d) Bunching coefficients



Note: Panel (a) and (b) reports the point estimate and the 95% (90%) confidence interval from a linear probability model using as outcome whether the individual/firm donated or not, using the characteristics displayed in the figure and election-specific fixed effects. The data for the estimation consist on matched individuals and firms using ORBIS and Riaño (2021), as well as not matched units (never-contractors and never-donors). Explanatory variables for firms are defined as dummies for whether a firm was above or below the median of the distribution. The coefficients for individuals include connected family, equal to one if the contractor have ever had a connection with a family member in the public sector. Education levels defined relative to *No formal studies*, and Experience defined as zero if *No experience*. Indicators for gender and age are included. Standard errors are clustered at the unit level. Panel (c) reports the distribution of (log) deviations from the minimum value contract threshold, excluding contract assigned via direct procurement, in bins of size 0.05 log deviations. The blue (red) line plots the observed distribution for donors (non-donors). Dashed lines plot the predicted distribution without the data within the excluded range. The gray lines indicates the minimum and maximum value of the excluded range. Panel (d) report the bunching estimates around the excluded range following Kleven and Waseem (2013), for donors and non-donors over mayoral cycles.

Szucs, 2023), suggesting mayors manipulate contract values to benefit their preferred contractors. We use the threshold for *minimum value* procurement below which contracts are less competitive. Thus, contracts around the threshold should be similar except for the mayors capacity to assign them.[12] We

[12]Except for direct allocations –bureaucratic contracts–, all procedures require some level of competition. The threshold separate minimum value contracts –less bids and faster assignment– from public tenders –more bids and longer time to

estimate the bunching size following Kleven and Waseem (2013); Kleven (2016), fitting a counterfactual distribution excluding the data around the threshold with equation $D_j = \sum_l^p \beta_j \cdot (z_j)^i + \sum_{j=-z}^{z+} \gamma_j \cdot \mathbb{1}[z_j = l] + \varepsilon_j$, where D_j is the number of contracts in the bin j, z_j is the deviations from the threshold in bin j, $z-$ and $z+$ are the excluded range, and p is the order of the polynomial. The excess bunching is obtained by comparing the counterfactual and observed distributions in the excluded range.

Panel (c) of Figure 4 shows the distribution of contracts relative to deviations from the (log) threshold, for donors (blue) and non-donors (red). The black dashed vertical line indicates the threshold. The gray vertical lines indicate the excluded range.[13] Dashed lines indicate the counterfactual distribution. We observe large bunching just below the threshold for both contractor groups, but larger bunching for donors than that of non-donors, indicating donors (and mayors) select into procurement avoiding competitive procedures to facilitate entry. Panel (d) formally estimates the bunching size for donors and non-donors by mayoral cycle, showing that donors always report larger bunching.

Donor Survival in Procurement Despite their lower performance and higher reliance on discretionary procedures, donors also experience an advantage in terms of persistence within the procurement system. Figure A5 plots Kaplan-Meier survival curves for donors and non-donors, measured from the first observed contract until the last recorded one. Donors exhibit substantially higher survival rates, remaining active for longer and exiting at lower rates once they obtain their first contract. This indicates that the benefits of donating extend beyond immediate contract allocation, conferring greater access to the procurement system.

4.2 Returns of Donating to a Political Campaign

4.2.1 Empirical Strategy

Having documented the systematic differences between donors and non-donors, we now move to the calculation of the returns to donating. To do so, we exploit within firm and within individual variation across electoral cycles using a stacked difference-in-differences design. Figure A4 illustrates the stacking procedure. The data is organized at the individual-by-half-year level from 2012 to 2023. For each election year (2015 and 2019), we construct a separate dataset that aligns time relative to the election. Individuals or firms who never donate provide the counterfactual evolution of outcomes, while individuals who donate contribute both pre-donation and post-donation observations within the same election event. We then stack these datasets so that the timing of treatment is standardized across cycles. Formally, we estimate

$$P_{i,t,s} = \gamma_{i,s} + \lambda_{t,m,s} + \beta \cdot (Donor_{i,s} \times Post_{t,s}) + \mathbf{X}_{i,t,s} + \varepsilon_{i,t,s}, \tag{1}$$

assignment–. See Appendix A.1 for details on all procurement procedures.

[13] The excluded range on both sides of the threshold is asymmetric, as it comes from a notch that changes the level of the distribution around the threshold (Kleven, 2016).

where indices i, t, and s denote individuals, half-years, and election events. $Donor_{i,s}$ equals one if individual i donates in election s. $Post_{t,s}$ equals one after election s. The interaction $Donor_{i,s} \times Post_{t,s}$ captures the moment when a given individual transitions from the pre-election to the post-election period within that cycle. The coefficient β therefore reflects the change in that individual's contracting outcomes after elections for donors, relative to the evolution observed for non-donors and donors in the pre-period in the standardized event timeline.

Individual-by-election fixed effects $\gamma_{i,s}$ absorb all time-invariant individual characteristics within each election event. Time-by-municipality-by-election fixed effects $\lambda_{t,m,s}$ absorb differential procurement trends across places and cycles. Standard errors are clustered at the individual level. The vector $\mathbf{X}_{i,s,t}$ includes the pre-election number of half-years since the unit has entered to the public procurement system and the cohort of entry (0 if no entry yet), which allow us to hold fixed selection into procurement by comparing units with similar experience and entry patterns. It also include an indicator for firms and individuals as each type might face different contract types.

The outcomes $P_{i,t,s}$ of interest include the probability of receiving a contract and the total value of contracts. We log-transform contract values following Chen and Roth (2022) to capture decreasing marginal returns and to accommodate zero values using the standard adjustment described in that literature.[14] Crucially, we drop the half-years when the elections occur (2015-2 and 2019-2) as from July to October, a procurement ban mechanically decreases the amount of contracts awarded, and during November and December, since we can not disentangle whether contracts were given by the current or incoming mayor.

The design relies on two assumptions. Parallel trends requires that, around elections, donors and non-donors would have exhibited similar outcome trajectories in the absence of elections, once we condition on the fixed effects and controls described above. No anticipation requires that contracting outcomes do not differentially respond to upcoming donations in the pre-election period; that is, there are no systematic pre-trends in outcomes for future donors relative to never-donors before the donation decision is realized.

4.2.2 Returns of Donating to a Political Campaign

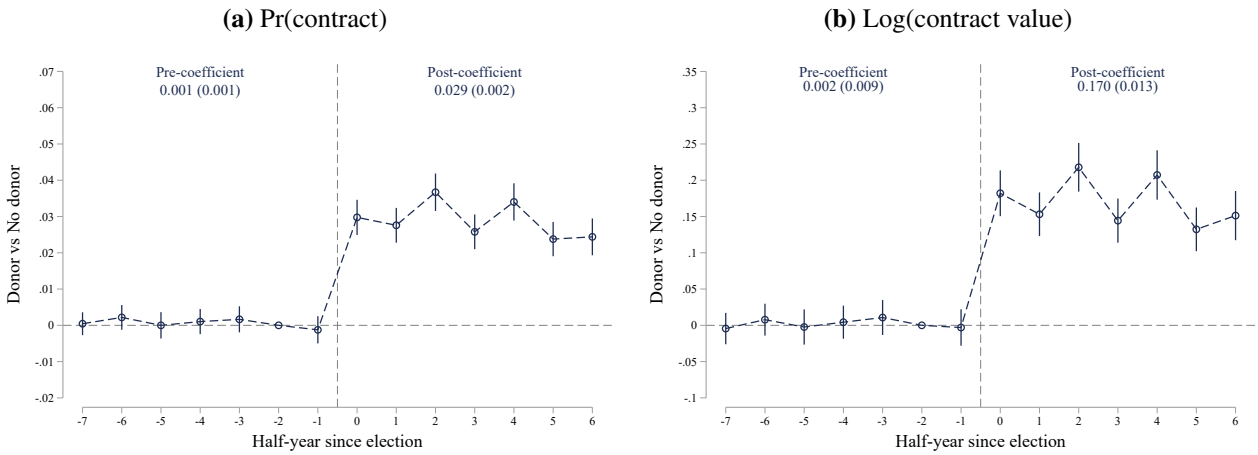
Figure 5 present the results from an event-study based on equation 1. At the top of each panel, we report the pooled coefficients for the pre and post periods. Panel (a) shows the results on the probability of receiving a contract. Panel (b) on the log-transformed contract value. Both show non-significant pre-coefficients (individually and pooled), supporting the parallel trends and no-anticipation assumptions. The figures show an immediate jump after the election.[15] In the extensive margin, the probability of receiving a contract after the elections is 2.8 percentage points higher for donors relative to non-donors,

[14] We normalize relative to the minimum non-zero value and assign $-x = -1$ for zeros. Moving from zero to a positive amount corresponds to approximately one hundred x log points in the intensive margin.

[15] These results are robust to variations of the intensive margin value in the log-transformation (Figure A6), and to not controlling for cohort of entry fixed effects that account for differential selection into procurement system (Figure A7).

equivalent to 28% of the non-donors mean before elections. In the unconditional intensive margin, we find that donors receive contracts with 17% greater value relative to non-donors after the elections. The coefficients support the hypothesis that donors receive significant returns from their contributions.[16]

Figure 5: Effect of Donating to a Political Campaign



Note: The figure reports the point estimate and the 95% confidence intervals from estimating an event study version of equation 1 for the overall population. It also reports the pooled coefficients for the periods before and after. Standard errors clustered at the individual level. The contract value is log-transformed. The intensive margin of the log transformation is defined following Chen and Roth (2022) and set to $x = -1$ for non-recipients. Pr(contract) equals one if the contractor reports having at least one contract per period.

An apparent limitation of our stacked difference-in-differences design is that it does not separately identify the effect of donations on electoral outcomes. In particular, our main estimand captures how contracting outcomes change for donors around elections, regardless of whether their preferred candidate wins or loses. This focus is intentional. Our empirical strategy is designed to study the returns to the decision to donate, relative to not donating, using within unit variation and the full universe of donors and non-donors. It therefore captures a different and broader treatment effect than the standard close-election regression discontinuity design, which focuses on the local comparison between donors to marginal winners and marginal runners-up.

We view this alternative estimand as substantively relevant for two reasons. First, from the perspective of firms and individuals deciding whether to enter campaign finance, the relevant question is not only "what is the return to backing the eventual winner near a zero margin," but rather "what is the expected return to donating at all, given uncertainty about the electoral result and the possibility that different candidates can still generate relational benefits." Second, our descriptive evidence shows that the advantages of donating are not confined to donors to winning candidates. As we document below, both our difference-in-differences estimates and event studies indicate that donors to winners

[16]Table A2 reports the average effect (β) from estimating equation 1. The results are robust to changing the assumption on the non-donor population. Table A3 show that the coefficients remain similar and significant if we drop from the non-donors those that would not have been able to donate due to lack of financial capacity.

and donors to runners-up obtain remarkably similar gains relative to non-donors, and that both groups enjoy substantial and persistent advantages in procurement (Figure A9). This pattern suggests that conditioning on electoral victory alone would miss an important margin of favoritism.

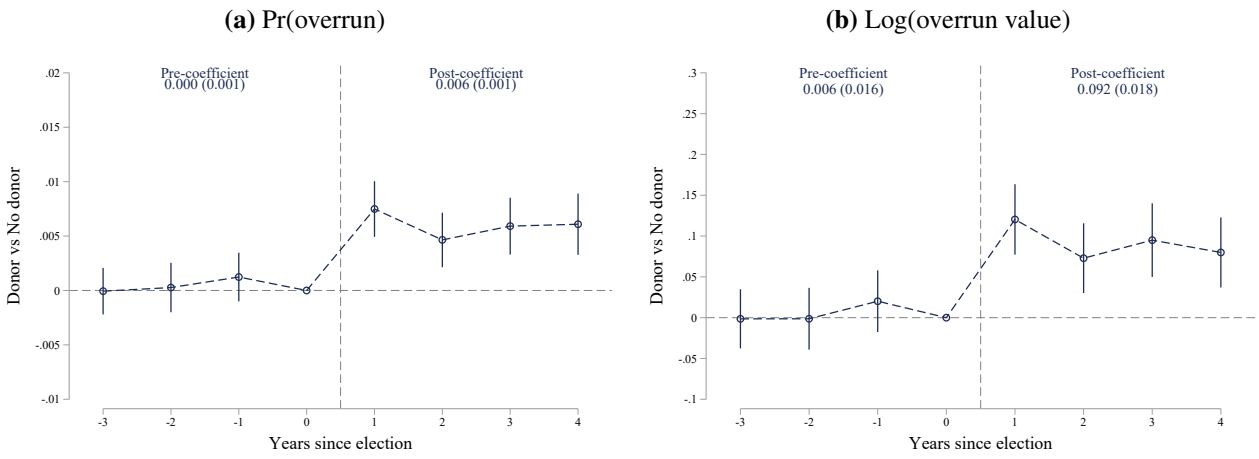
To benchmark our results against the existing literature, we nonetheless implement a close-election regression discontinuity design in the spirit of Colonnelli, Prem and Teso (2020). In that design, we compare donors to winning candidates and donors to runners-up in races decided by very small vote margins. Consistent with prior work, we find that donors to winners earn higher returns than donors to runners-up at the zero vote margin (Figure A8). Our difference-in-differences estimates show the same ranking of returns by candidate status, and restricting the sample to close elections yields event-study patterns that closely mirror our baseline results (Figure A10). Taken together, these findings indicate that our stacked design produces estimates that are aligned with close-election evidence where the two approaches overlap, while also revealing that the advantages of donating extend well beyond the narrow set of marginal races and donors typically captured by an RDD.

Efficiency Consequences of Political Donations Donors reporting less efficient contract execution can indicate distortions in public resources allocation (Mironov and Zhuravskaya, 2016; Schoenherr, 2019; Baranek and Titl, 2020; Ruiz, 2021). This is more likely considering that contractors selecting into donation are worse than non-donors, and are more likely to avoid competitive procedures (see section 4.1). Figure 6 report the results from estimating an event study based on equation 1 using the probability and value of overruns as a proxy for inefficient behavior and aggregating the data at the individual-by-year level as overruns are infrequent events (10%, see Table 1). The coefficients show that donors have a one percentage point higher probability of reporting an overrun (5.3% of non-donors mean conditional on overrun) and close to 10% higher overrun value than non-donors, suggesting that donors increase their returns by extending their contracts, distorting the overall contract allocation.

Our variables approximate distortions, but do not fully capture them. Well-planned contracts might still have overruns, and contract extensions can be allowed. Yet, differences in overruns are major, so interpreting the contracts assigned to donors as inefficient also captures donors' capacity to extract rents. To further test for rent-extraction behavior, we separate the contracts between discretionary (direct and minimum value contracts) and non-discretionary (public-tenders), as higher discretion can lead to misallocation (Baltrunaite et al., 2021; Bosio et al., 2022), and show that the returns of donating are present only in discretionary procedures (Figure A13).

Pay-to-play and Sustained Access to Public Procurement Because mayors cannot be reelected, persistent returns after the mayoral period has ended might signal that donations can act as investments that enable access to procurement. We label this mechanism "pay-to-play". We test for it by estimating

Figure 6: Effect of Donating to a Political Campaign - Efficiency of Contracts



Note: The figure reports the point estimate and the 95% confidence intervals from estimating an event study version of equation 1 for the overall population. Standard errors clustered at the individual level. The contract value of the overrun is log transformed. The intensive margin of the log transformation is defined following Chen and Roth (2022) and set to $x = -1$ for non-recipients. Pr(overrun) equals 1 if the contractor had at least one contract with an overrun per period.

effects separately for the 2015 and 2019 elections, extending both event panels to all post-periods.[17] Panel (a) in Figure 7 reports the results on contract values. We find that 2015 donors (blue coefficients) perceive returns the mayoral election after the donation. The immediate effect is 16.4% greater contracts compared to non-donors, while the next mayoral period effect is 13.9%. The decrease between periods suggest that quid-pro-quo interactions still matter, but the returns indicate that donation is an investment for long-term access. The returns are long-lasting even if there are ideological changes in the government (Figure A12).[18]

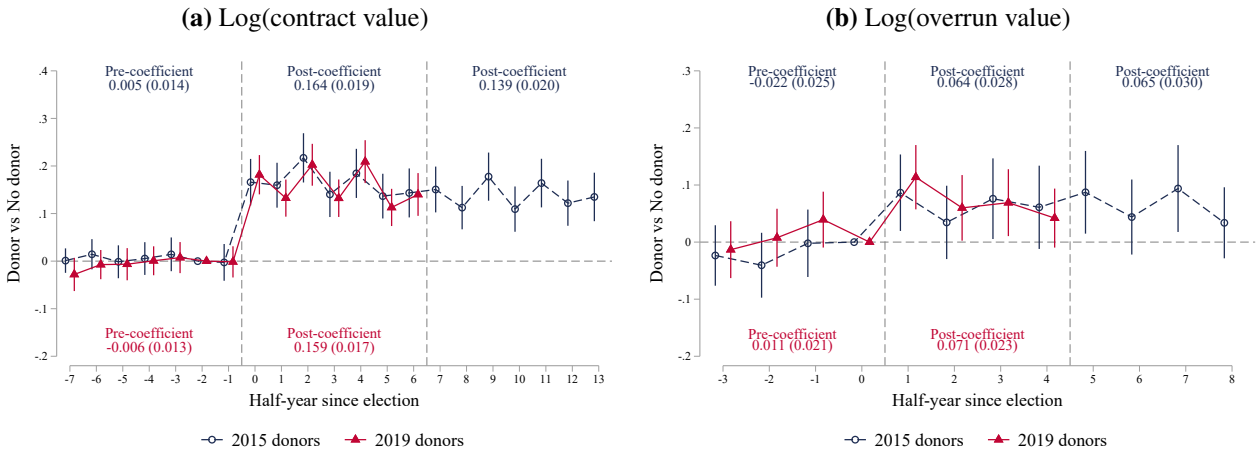
Panel (b) show the results for the yearly overrun value. The effects for the 2015 donors is positive and significant for the two mayoral periods after the donation. We find that donors perceive 6.5% greater cost overruns compared to non-donors, indicating that donors do not require continued connection with the mayor to whom they donated to extract larger rents from their contracts. As such, political campaign contributions lead to long-term distortions in contract allocation. In line with this, there are also long-term effects for discretionary contracts (Figure A13). In both panels, the coefficients for the 2019 donors shows an increase of similar magnitude.[19]

[17] By separating the estimation by event-panel, we drop the indicators for each event-panel from equation 1. Because we do not have staggered timing, we estimate the effects through two-way fixed effects.

[18] Titl and Geys (2019) show that donors of winning parties receive higher-valued contracts. One interpretation is that donors might be punished if the party leaves office. We explore these dynamics separating between municipalities that change / not change the party in power in the 2019 elections using data on political parties characterization from Cabra-Ruiz et al. (2023).

[19] Figure A11 report the results for the probability of receiving a contract and probability of reporting and overrun. The results are consistent for the extensive margin.

Figure 7: Long-term Effect of Donating to a Political Campaign



Note: The figure reports the point estimate and the 95% confidence intervals from estimating an event study based on equation 1 independently for each election sub-panel, and extending for each the respective post periods. Blue coefficients are for the 2015 elections. The red coefficients are for the 2019 elections. It also reports the pooled pre and post coefficients. Standard errors clustered at the individual level. Panel (a) for the log-contract value aggregates the data at the individual-by-half-year level. Panel (b) for the log-overrun value aggregates the data at the individual-by-year level. The contract value and overrun are log transformed. The intensive margin of the log transformation is defined following Chen and Roth (2022) and set to $x = -1$ for non-recipients.

5 Information Asymmetries and Curbing the Influence of Donations

A natural question at this point is why the previous documented distortions persist. While existing work have studied policies that exclude donors from procurement (Baltrunaite, 2020; Avis et al., 2022; Gulzar, Rueda and Ruiz, 2022), our focus turns to the incentives and informational frictions that allow politicians to continue favoring their donors despite these regulations.

Building on the empirical results and on qualitative evidence from prior fieldwork, our premise is that these distortions persist because both mayors and their oversight principals operate with incomplete and asymmetric information. The nationwide experiment we implement is designed to identify which specific informational gaps sustain favoritism and to evaluate whether these frictions can be weakened at scale.

To guide the experimental design, we posit four mechanisms through which information asymmetries may allow donor favoritism to continue. First, favoritism may stem from mayors' limited knowledge of the legal restrictions governing contracting with donors.[20] Second, distortions may persist if mayors believe oversight bodies lack the capacity to monitor and sanction irregularities.[21]

[20]Prior work shows that targeted information can improve public sector performance (Hjort et al., 2021; Saavedra, 2024)

[21]This belief accords with evidence of the limited ability of national institutions to follow procurement across thousands of municipalities (MOE, 2018).

Third, even when capacity exists, mayors may assume principals will seldom use it, either because deploying it is costly or because principals lack the concrete signals needed to detect wrongdoing. Fourth, favoritism can endure even when information and capacity are available if mayors cannot credibly convey to donors that effective monitoring is in place at the moment a favor is requested. Without such a credible signal, refusing a request may be interpreted as unwillingness rather than constraint.

To test these hypotheses, we partnered with the Open Contracting Partnership (OCP), the Instituto Anticorrupción (IA), and the Office of the Inspector General in Colombia to implement a nationwide randomized controlled trial.[22] The intervention delivered letters to newly elected mayors after the 2023 municipal elections. These letters reminded mayors of the legal framework governing political finance and the restrictions on contracting with donors. They also used publicly available data on procurement and campaign contributions to signal the oversight capacity of authorities and to inform mayors that donor related contracting could be monitored and verified. The design and primary outcomes were preregistered in the AEA RCT Registry.[23]

5.1 Experimental Design

Figure 8 shows the intervention, with the number of units in each treatment arm in parentheses. We randomize municipalities where at least one candidate reported receiving a donation in the 2023 mayoral campaign. Mayors in treated municipalities receive a **Letter** from OCP and IA containing information about campaign financing regulations and restrictions on donors' participation in public procurement. The letter is divided into treatment arms that vary in whether it also informs about increased oversight. The base treatment, **Letter + No CC**, includes only the regulatory framework to tests if improved knowledge alone affects mayors' procurement decisions.

To test if favoritism persists due to limited monitoring capacity, the **CC Investigative Journalist** and **CC Inspector General** treatments add to the letter a header naming the oversight agent and highlight increased monitoring by noting that they will follow donors' procurement outcomes. We expect mayors to reduce donors' contract assignments when monitoring comes from an authority capable of sanctioning misbehavior.

Even with monitoring capacity, distortions may persist if oversight is not credible and agencies cannot held politicians accountable. To test for 'credibility', we further divide treatments into subgroups. Mayors in the **No donor list** treatment receive only the letter. Mayors in the **Donor list** arm additionally receive an attachment listing all donors to any candidate in the last mayoral election, along with their procurement history. This arm enhances the credibility of the letter by demonstrating that authorities have concrete, actionable information linking donors and contractors.

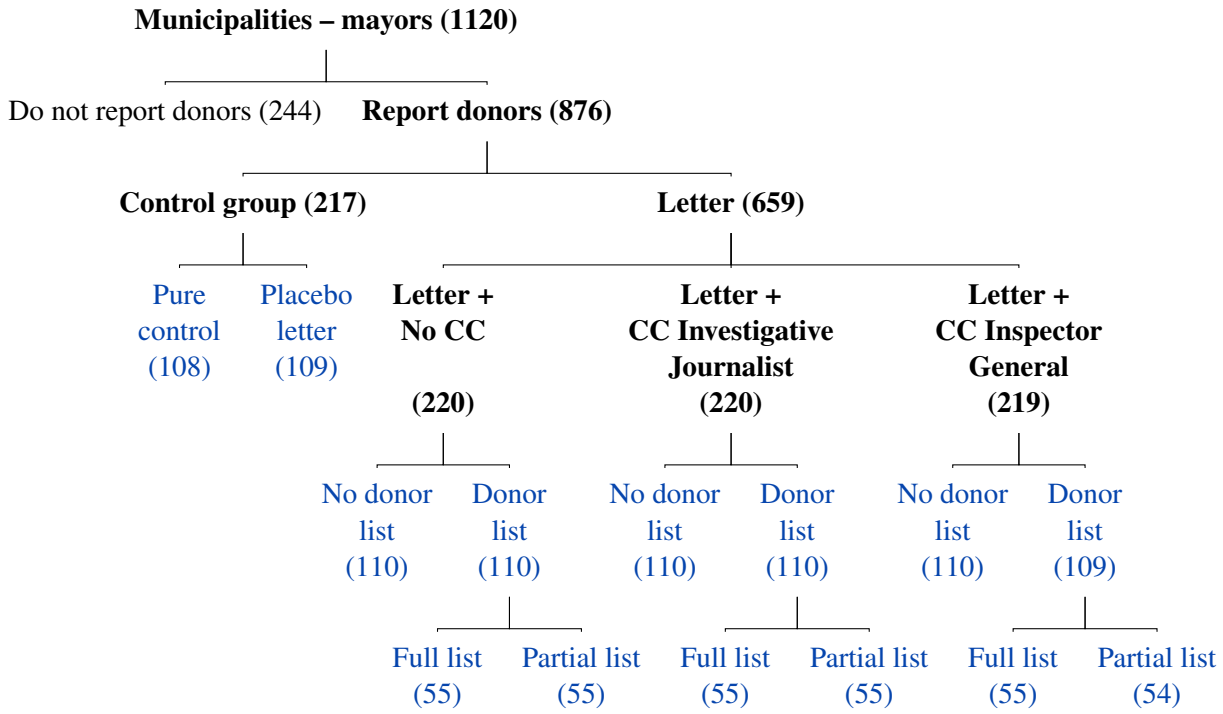
[22] OCP is an international NGO dedicated to improving procurement through open data. IA is a Colombian anti-corruption NGO. Appendix B.1 provides additional details on each partner organization.

[23] AEA RCT Registry number AEARCTR-0013709.

Finally, the donor list may also create a plausible deniability: mayors can justify denying contracts to donors only when oversight agencies observe them. Thus, favoritism may persist if some donors remain hidden. To test this mechanism, we include a **Partial Donor List** treatment, where one donor per candidate is omitted. This generates random variation in which donors are 'visible' to oversight, allowing mayors to continue favoring those not listed.

The control municipalities consist of two groups. Mayors in the **Pure Control** group receive no letter, while those in the **Placebo** group receive a letter only describing the partner NGOs, allowing us to test whether mayors react to *any* seemingly relevant communication. Table B5 in the appendix show that the placebo letter had no effects, so we combine it with the pure control into a single control group for subsequent analyses.

Figure 8: Experimental Design - Treatment Arms



Note: The figure illustrates the treatment arms structure of the experimental design. The number of municipalities (i.e., mayors) included in each treatment arm is reported in parentheses.

Implementation Details Figure 9 describes the timeline. Mayoral elections for the period 2024-2027 were held in October of 2023. Elected candidates assumed office in January 2024. Our analysis spans the first year of the mayoral period. E-mail letters were sent May, and physical letters were sent three months after as a remainder.[24] We tracked interactions with the e-mail and found that 100%

[24]The information used for mayoral e-mails and physical addresses is public available. It was compiled from the *National Information System of Public Employment*. In cases where the e-mail or physical address was incorrect, we obtained the information from the institutional web pages of the municipalities.

of the letters were received and opened (see Table B1). 80% of the physical letters arrived at their municipality within the first week, and 95% after three weeks. Because all communications received by a public office should be re-directed to the individual to whom it is addressed, we can be confident that the letters reached the mayor's mailbox.

Figure 9: Experimental Design - implementation timeline

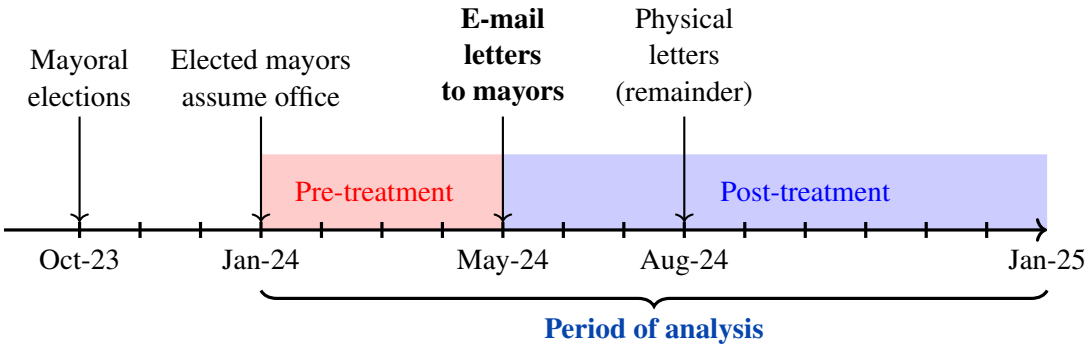


Figure B1 shows the letter variation across treatment arms. All letters mention that OCP and IA intend to remind mayors about the legal framework on public procurement and political campaign donors, followed by a short description of such legal framework. For municipalities randomized into **CC Investigative Journalist** or **CC Inspector General** treatments, the header of the letter mentions the oversight agent, and concludes noting that donors' public procurement information will be shared with them. For municipalities in the **Donor list**, the letter includes a paragraph describing the attachment. Figure B2 shows an example of the list attached to the letter.

Randomization The intervention consists of 876 municipalities randomized across 11 treatment arms. Municipalities are placed in 57 blocks based on the number of unique contractors, the total contracted value, and the share of the value assigned to donors, all measured in the previous mayoral period (2020-2023). We build equally sized blocks –randomization strata– by sorting the three variables. All treatments are randomized at the municipal level within each block.[25] For municipalities receiving a partial list of donors, we randomly select the ones to be excluded. We build blocks based on the rank of the candidate –winner, runner-up, or any other–, so a donor is randomly excluded for each rank within the municipality.[26] Appendix B.3 show we have balance in municipal and donor level covariates.

5.2 Estimating Equation

The intervention intends to decrease the information asymmetries of politicians expectation about monitoring and oversight. If decreasing improving the information environment is effective to curb

[25]The size of each block is 16 municipalities, except for one which is of size 28.

[26]We obtained 1,189 blocks of at least two donors, one of which is randomly excluded from the attachment sent to mayors. Some blocks were formed with observations across municipalities because of data sparsity.

favoritism, we would expect lower procurement outcomes for donors in municipalities where the mayors received a letter. Lower returns of donating can also be reflected in the distribution of contracts towards other non-donors, suggesting that reduced information asymmetries causes a system-level effect where the resources are allocated to other participants.

We follow the public procurement outcomes for donors and non-donors, before and after the letters have been sent. We aggregate our panel data at the individual-by-*month* level as described in section 3 for the first year of the mayoral period. We estimate equations of the form:

$$P_{i,t} = \gamma_i + \lambda_{m(i)\times donor\times t} + \sum_{j}^{J} \beta_{donor}^{j} \left(\mathbb{1}[\text{Letter}_{m(i),donor} = j] \times \text{Post}_t \right) + \sum_{j}^{J} \beta_{nondonor}^{j} \left(\mathbb{1}[\text{Letter}_{m(i),nondonor} = j] \times \text{Post}_t \right) + \varepsilon_{i,t}, \quad (2)$$

$P_{i,t}$ is the procurement outcome for i (donor or non-donor) in month t, defined as in Section 4.2. Post_t equals one for the periods after the letters were sent and zero before. $\mathbb{1}[\text{Letter}_{m(i),donor} = j]$ equals one for donors in municipality m where the mayor received the letter of treatment j, and zero otherwise. In our preferred specifications $Letter_{m(i),donor}$ consist of six independent dummies, for mayors receiving the letter with and without list, for each oversight agent. β_{donor}^{j} capture the effect of the letter. If it is negative, we conclude that treatment j decrease the influence of political donations compared to the control group.

For non-donors, the term $\mathbb{1}[\text{Letter}_{m(i),nondonor} = j]$ consider the aggregate effects from the oversight agents as the only relevant treatment for them is whether the mayor received a letter. We include γ_i as an individuals i fixed effect, and $\lambda_{m(i)\times donor\times t}$ as a municipal randomization block $\times$ $\mathbb{1}[Donor]$ $\times$ time fixed effects. Because the randomization and donation status are constant for individuals, they are absorbed by the individual fixed effects. By including $\lambda_{m(i)\times donor\times t}$, we are able to account for specific differential time trends across randomization structures and by donation status. $\varepsilon_{i,t}$ is for the standard errors clustered at the municipal level.

5.3 Decreased Information Asymmetries and Returns of Donating

Table 2 presents the results of estimating equation 2. Columns 1–2 report effects on the probability of receiving a contract, and columns 3–4 on log contract value. The first column for each outcome (1 and 3) reports the aggregate treatment effect, while the second (2 and 4) separates treatments with and without the donor list.

We find significant effects only when the letter mentions the Office of the Inspector General *and* includes the list of donors. The coefficients indicate a 0.7 percentage point reduction in the probability that a donor receives a contract (about 30% of control donors dependent variable), and a 4.3% decrease in contract value relative to donors in control municipalities. Letters mentioning the Investigative

Journalist or containing no oversight mention show no significant results regardless of the donor list. We also find no effects for non-donors, suggesting that decreased favoritism does not spillover to other procurement participants.

The bottom rows of the table report p-values comparing the *Inspector General + list* effect with the other treatment arms. The difference relative to *Inspector General + no list* is significant, indicating that oversight reduces favoritism only when the threat is made credible through actionable information. The difference relative *Investigative journalist + list* is also significant, showing that the identity of the oversight agent matters. We cannot reject a difference relative to the *No CC + list* treatment arm, although their difference is in the expected direction. The difference relative to non-donors is significant, underscoring that the effect is sizable. Overall, the results show that highlighting government monitoring capacity and attaching the donor list to signal oversight credibility, effectively decreases the short-term returns to political donations.

We next examine how these effects evolve over time by estimating coefficients for each post-treatment period. Figure 10 presents the results for the Inspector General treatment (Figure B3 show the remaining treatments). Panel (a) reports estimates for the list treatment and Panel (b) for the no list treatment. The coefficients after the intervention are significant only for the treatment letter with the donor list, with magnitudes sustained around and are sustained around 8% and 10% throughout the year. This dynamic suggest that credible oversight improves procurement allocation for up to nine months later, covering the full extent of a procurement cycle in our data.

Table B6 in the Appendix separates effects for the partial list (*omitted donor*) and full list (*included donor*) treatments. Both coefficients are negative in the *Inspector General + list* arm, but only the effect for *included donors* is significant. Yet, the difference between included and omitted donors is not significant, indicating no evidence that mayors deny preferential treatment to "hidden" donors.

Differential Effects by Rank of Supported Candidate Mayors may respond more strongly to their own donors' procurement outcomes if they anticipate that they are more likely to be scrutinized. This is consistent with donors to the elected mayor receiving larger returns (as discussed in Section 4.2). We estimate a variant of equation 2 in which each treatment arm is split by whether the donor supported the winner or a non-winner. We include donor randomization block fixed effects to compare donor groups supporting the same candidate rank across municipalities.

Panel A of Figure B4 in the Appendix shows that effects are negative and significant for donors to the winner for all oversight agents mentioned in the letters. When separating *list* or *no list* treatments, all coefficients remain negative, and the *Inspector General + list* effect remains significant. The p-values at the bottom indicate no significant differences between the *list* treatments for the winning candidate. These patterns are consistent with donors to the winner having a direct relationship with public officials, making any credible oversight threat effective. Effects for donors to non-winning candidates are smaller in magnitude and significance.

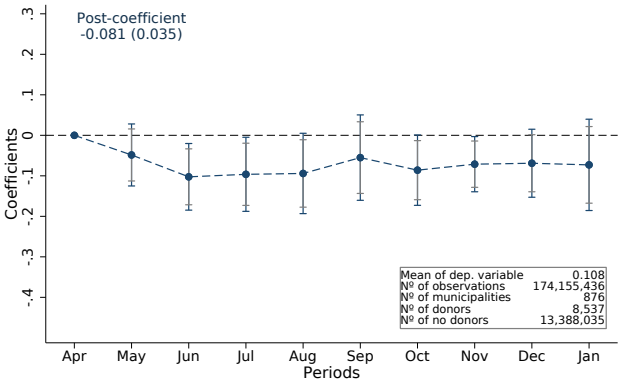
Table 2: Effect of RCT Letter on Procurement Outcomes

Dep. Variable	Pr(contract)		Log(contract value)	
	(1)	(2)	(3)	(4)
Donor				
A. Inspector General×Post	-0.003		-0.018	
	(0.002)		(0.014)	
Inspector General + no list×Post		0.001		0.004
		(0.002)		(0.015)
Inspector General + list×Post		-0.007**		-0.043**
		(0.003)		(0.019)
B. Investigative Journalist×Post	-0.002		-0.014	
	(0.002)		(0.014)	
Investigative Journalist + no list×Post		-0.002		-0.014
		(0.003)		(0.018)
Investigative Journalist + list×Post		-0.002		-0.015
		(0.002)		(0.015)
C. No CC×Post	-0.002		-0.017	
	(0.002)		(0.015)	
No CC + no list×Post		-0.001		-0.016
		(0.003)		(0.018)
No CC + list×Post		-0.002		-0.017
		(0.003)		(0.018)
Non donors				
A. Inspector General + NO donor×Post	-0.000	-0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)
B. Investigative Journalist + NO donor×Post	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)
C. No CC + NO donor×Post	0.000	0.000	0.002	0.002
	(0.000)	(0.000)	(0.003)	(0.003)
Linear combinations P-values				
A. Inspector General - B. Investigative Journalist			0.758	
A. Inspector General - C. No CC	0.751		0.894	
Inspector General + list - Inspector General + no list		0.025		0.016
Inspector General + list - Investigative Journalist + list		0.156		0.144
Inspector General + list - No CC + list		0.240		0.211
A. Inspector General + donor - A. Inspector General + NO donor	0.254		0.213	
Inspector General + list + donor - Inspector General + NO donor		0.039		0.025
Mean dependent variable for donors	0.024	0.024	0.425	0.425
N. of obs.	174,155,488	174,155,488	174,155,488	174,155,488
Number of municipalities	876	876	876	876
Number of donors	8,537	8,537	8,537	8,537
Number of Non donors	13,388,039	13,388,039	13,388,039	13,388,039
Individual FE	Yes	Yes	Yes	Yes
Block × $\mathbb{1}[Donor]$ × Time FE	Yes	Yes	Yes	Yes

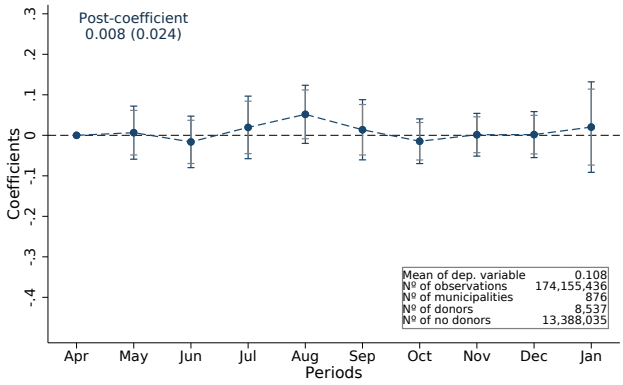
Notes: The unit of analysis is the individual-month, estimating equation 2 on procurement outcomes. *Inspector General* is for the treatment letter carbon copying the relevant public office that oversight public procurement. *Investigative Journalist* is for the treatment letter carbon copying investigative journalist. *No CC* is for municipalities receiving the treatment letter without carbon copy additional organizations. *No list* is for treatment letters not including the donor list as attachment. *List* group the treatment letter including the full and partial list of donors as attachment. *Pr(contract)* equals 1 if the donor received a contract in t, 0 otherwise. *log(contract value)* is the value of contracts. The log transformation follows Chen and Roth (2022) and define the intensive margin as $x = -1$ for non recipients. *Post* equal 1 for periods after the letter were sent to mayors. The mean of the outcomes is measured in the pre-period and is reported in million COP for the contract value. *Individual FE* is for individual fixed effects. *Block* × $\mathbb{1}[Donor]$ × *Time FE* is for randomization block by donation status by month fixed effects. Standard errors clustered at the municipal level are in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 10: Effect of RCT Letter on Procurement Outcomes – log(Contract Value)

(a) Inspector General + list



(b) Inspector General + no list



Note: The unit of analysis is the individual-month. The figure shows point estimates and the 90% and 95% confidence intervals from estimating equation 2 on procurement outcomes. Coefficients only reported for donors. Fixed effects for randomization block $\times$ $\mathbb{1}[Donor]$ $\times$ month are included. Standard errors clustered at the municipality level. The point estimates represent the effect of the treatments relative to the *Control* groups post-intervention. The outcome is the *Log(contract value)*. The log transformation for the value follows Chen and Roth (2022), defining the intensive margin as $x = -1$ for non-recipients.

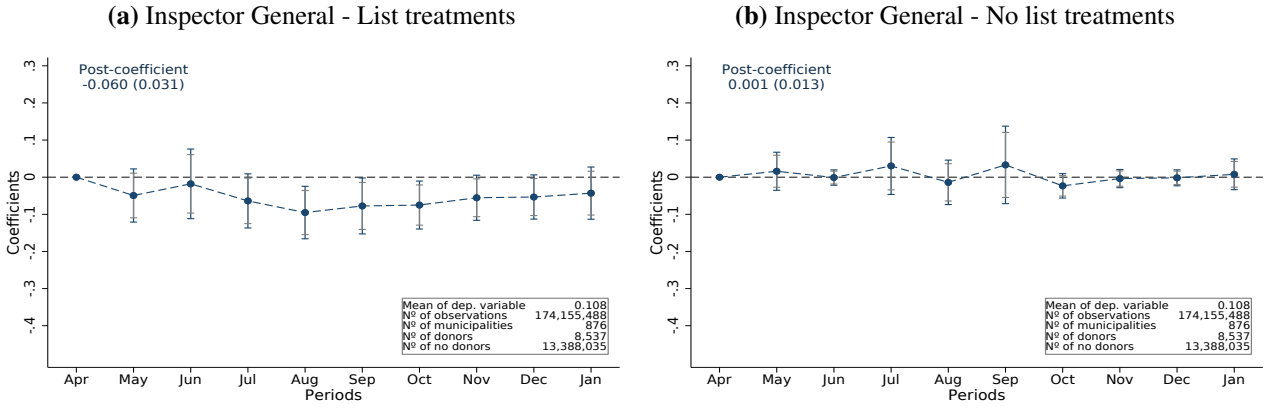
Returns to Previous Election Donors Section 4.2 shows that donors "pay" to get long-term access to public procurement, resulting in persistent distortions. We assess if increased monitoring with credible oversight changes the mayors' incentives to allocate contracts to donors from the previous election, for which a direct political link might not be observed due to political turnover. We estimate equation 2 separating the previous election donors (pay-to-play) from the non-donors. Because there is no donation overlap across mayoral races, the donor list attached to the letter never includes from earlier elections.

Panel B of Figure B4 in the Appendix shows no significant effects on previous election donors' procurement outcomes. Thus, despite communications coming from the government including actionable information can break the influence of money in politics for new donors, it does not alter contracts allocation to previous election donors. As such, the absence of effects highlights the importance of early intervention to avoid long-term distortions.

Reduced Information Asymmetries and Procurement Efficiency Section 4.2 shows that donors experience more overruns than non-donors, suggesting distortions in contract allocation. We estimate the effects of the intervention on these efficiency proxies. Figure 11 show the post-treatment coefficients for the *Inspector General + list* arm (Figure B5 shows the remaining treatments), with the caveat that overruns are recorded a few months after a contract is issued, so we cannot fully capture them. The coefficients indicate a decrease in overrun value around 6% significant thought the procurement cycle. Suggesting that improved monitoring with credible oversight reduces inefficiency in public contract execution.

We next examine how the intervention affects favoritism in discretionary procurement. Panel C of Figure B4 reports the results separating by discretionary and non-discretionary procedures and shows that the *Inspector General + list* treatment reduces discretionary contracts awarded to donors. Panel D considers contracts assigned just below the minimum value procurement threshold, where we documented bunching in 4.1. Donors in the *Inspector General + list* receive less contract value close to the threshold. Overall, the shows to improve procurement efficiency.

Figure 11: Effect of RCT Letter on Procurement Efficiency – log(Overrun Value)



Notes: The unit of analysis is the individual-month, estimating equation 2 on the overrun value. *Inspector General* is for the treatment letter carbon copying the relevant public office that oversight public procurement. *Investigative Journalist* is for the treatment letter carbon copying investigative journalist. *No CC* is for municipalities receiving the treatment letter without carbon copy additional organizations. *No list* is for treatment letters not including the donor list as attachment. *List* group the treatment letter including the full and partial list of donors as attachment. The outcome *log(overrun value)* is the value of overrun. The log transformation follows Chen and Roth (2022) and define the intensive margin as $x = -1$ for non-recipients.

Unintended Consequences in Municipal Procurement A potential unintended consequence of the intervention is that mayors might reduce overall procurement to avoid complaints about of public resources, which could harm municipal performance despite curbing favoritism. To assess this, we aggregate the individual-by-month data to the municipality-by-month level and estimate a reduced version of equation 2 with municipality fixed effects and block-by-month fixed effects. Table B7 in the Appendix shows no significant effects on the (log) total value of contracts awarded to non-donors, indicating that mayors did not respond by reducing overall procurement spending.

6 A Model of Political Donations and Public Procurement

We develop a dynamic structural framework to formalize the economic incentives that sustain the link between political donations and public procurement. The experimental evidence in Section 5 shows that reducing information asymmetries and strengthening credible oversight can curb favoritism in the moment. Yet the reduced-form results also make clear that donor advantages persist as long as contributing remains a profitable strategy for firms. Understanding the roots of this profitability

requires a model that traces how the informational frictions documented earlier interact with firms' forward looking decisions over electoral cycles.

Motivated by these patterns, we propose a discrete choice model in which firms decide whether to enter the procurement market and whether to donate during election years. Donations involve a sunk cost that may generate differential production costs or soften competitive pressure, and firms weigh these potential advantages against the risks that oversight imposes. This structure allows us to identify the hidden costs that shape firms' dynamic participation decisions and to quantify the economic mechanisms that link political giving to contract allocation.

The model follows the empirical regularities uncovered in earlier sections. As described in Section 3, procurement exhibits high turnover, with entry and exit clustered around election cycles. Contracts awarded after elections tend to accrue to donors, yet only a small share of contractors ever donate despite these observed returns. To account for this pattern, we introduce heterogeneous costs for donors and non donors that affect both their propensity to contribute and their likelihood of remaining active in procurement. Firms' decisions are modeled as forward looking investments that depend on expected procurement opportunities, political turnover, and idiosyncratic shocks that influence their transitions across donor and non donor states.

6.1 Model Structure

Timing Time is discrete with finite horizon ($t = 0, 1, 2, \ldots, T$) and finite number of incumbent firms i participating in public procurement.[27] Firms decide to donate (D) or not (O). At any period t, each incumbent firm is in one of four states $s_{it} \in \{OO, OD, DO, DD\}$, where the first position indicates if the firms donated (or not) in the previous election, and the second indicates if firms donate (or not) in the upcoming elections.[28] The state of the market at time t is represented by the aggregation $s_t \equiv \{s_{it}\} = (N_t^{OO}, N_t^{OD}, N_t^{DO}, N_t^{DD})$, indicating the number of firms in each state.

The model begins in $t = 0$ with $N_0^{OO}, N_0^{DO} \geq 0$ incumbents who are currently non-donors, and no firms donating for the upcoming election, $N_0^{OD} = N_0^{DD} = 0$. Each $t > 0$ starts with firms sequentially entering the public procurement system until the expected value of entry falls below the entry cost κ^{ent}. Incumbents may exit, stay, or stay and donate to the upcoming election by paying a sunk cost κ to procure services at a different production cost after elections.[29] A current donor decides to exit or stay. Active firms also incur in state specific fixed costs (or fringe benefits) of operation ϕ. The following features of the game are common knowledge:[30]

[27] We take individual contractors as sole proprietorship firms, as is usually assumed in public procurement.

[28] (i) OO is for firms not donating in the previous and incoming elections. (ii) OD is for not donors in the previous election but donors in the upcoming campaign. (iii) DO if for donors in the previous election but not donors in the upcoming campaign. (iv) DD is for firms donating in the previous and upcoming elections

[29] The marginal cost difference reflects the relative advantage or disadvantage of donating. The greater the market share of donors relative to non-donors, the lower the implied marginal cost for donors.

[30] Our model and solution builds and expand upon Igami (2018), which examines the industry dynamics of offshoring. Similar to offshoring decisions, political donations entail sunk costs aimed at securing a competitive advantage in public

1. Each t starts with free sequential and costly entry, followed by competition where each firm earns profit $\pi_t(s_{it}, s_{-it})$ based on public sector demand and cost conditions.

2. Then, incumbents N_t^{OO}, N_t^{DO} simultaneously choose a_{it}^{OO}, a_{it}^{DO} (exit, stay or stay and donate) and draw i.i.d *private cost shocks* $\varepsilon_{it}^{OO} = (\varepsilon_{it}^{1,OO}, \varepsilon_{it}^{2,OO}, \varepsilon_{it}^{3,OO})$, $\varepsilon_{it}^{DO} = (\varepsilon_{it}^{1,DO}, \varepsilon_{it}^{2,DO}, \varepsilon_{it}^{3,DO})$. Donating firms N_t^{OD}, N_t^{DD} follow by simultaneously choosing $a_{it}^{OD}, a_{it}^{DD} \in \{\text{exit, stay}\}$ and draw i.i.d shocks $\varepsilon_{it}^{OD} = (\varepsilon_{it}^{1,OD}, \varepsilon_{it}^{2,OD})$, $\varepsilon_{it}^{DD} = (\varepsilon_{it}^{1,DD}, \varepsilon_{it}^{2,DD})$

3. Market structure transits from s_t to s_{t+1} based on the firms' actions

Private cost shocks arise from firm's idiosyncratic but transient conditions. We focus on anonymous, type-symmetric pure strategies that convert these into discrete choices (similar to a static entry game with private information). We assume ε_{it} are i.i.d type-1 extreme value with scale parameter ρ.

Per-period Profit Profit $\pi_{it} = \pi(s_{it}, s_{-it}, D_t, C_t)$ is determined by the public sector demand D_t, production cost C_t, the firm's state s_{it}, and the other firms' states s_{-it}. The demand D_t links the aggregate value and quantity of contracts, while the cost function represents the relationship between each firm's output and production costs. D_t and C_t are recovered from the data. We assume Cournot competition and analyze an anonymous, type-symmetric Nash equilibrium. As a result, the market structure s_t, which includes s_{it}, D_t and C_t, fully determines each firm's equilibrium profit during the competition stage. This method allows us to address the dynamic game of donation and entry decisions within a compact state space, despite the large number of firms observed in the data.

Firms' Problem Firms make dynamic discrete choices to maximize their expected values. The future profits are discounted by $\beta \in (0,1)$, maintaining rational expectations about the endogenous evolution of the market and the exogenous evolution of demand and production costs. The expectations are over the other firms' choices, and hence over the realizations of their private cost shocks. The dynamic programming problem of active firms in $s_{i,t} = OO$ and $s_{i,t} = OD$ is:

$$V_t^{OO}(s_t, \varepsilon_{it}^{OO}) = \pi_t^{OO}(s_t, \cdot) + \max_{a_{i,t} \in \mathscr{A}} \begin{cases} \varepsilon_{it}^{1,OO} & \text{if } a_{i,t} = \text{exit} \\ \phi^{OO} + \beta \mathbb{E}\left[V_{t+1}^{OO}(s_{t+1}, \varepsilon_{it+1}^{OO}) | s_t, \varepsilon_{it}^{OO}\right] + \varepsilon_{it}^{2,OO} & \text{if } a_{i,t} = \text{stay} \\ \phi^{OD} + \beta \mathbb{E}\left[V_{t+1}^{OD}(s_{t+1}, \varepsilon_{it+1}^{OD}) | s_t, \varepsilon_{it}^{OO}\right] - \kappa + \varepsilon_{it}^{3,OO} & \text{if } a_{i,t} = \text{donate} \end{cases}$$

$$V_t^{OD}(s_t, \varepsilon_{it}^{OD}) = \pi_t^{OD}(s_t, \cdot) + \max_{a_{i,t} \in \mathscr{A}} \begin{cases} \varepsilon_{it}^{1,OD}, & \text{if } a_{i,t} = \text{exit} \\ \phi^{OD} + \beta \mathbb{E}\left[V_{t+1}^{OD}(s_{t+1}, \varepsilon_{it+1}^{OD}) | s_t, \varepsilon_{it}^{OD}\right] + \varepsilon_{it}^{2,OD} & \text{if } a_{i,t} = \text{stay} \end{cases}$$

procurement. Firms studied by Igami (2018) incurred in substantial relocation costs to reduce production expenses. Likewise, political donations can be seen as strategic investment, positioning firms favorably–much as offshoring serves as a cost-reducing investment essential for competitiveness in a global oligopoly. In the baseline model, however, we are agnostic about the direction of the implied effect.

The dynamic programming problem of active firms in $s_{i,t} = DO$ and $s_{i,t} = DD$ is:

$$V_t^{DO}(s_t, \varepsilon_{it}^{DO}) = \pi_t^{DO}(s_t, \cdot) + \max_{a_{i,t} \in \mathscr{A}} \begin{Bmatrix} \varepsilon_{it}^{1,DO}, & \text{if } a_{i,t} = \text{exit} \\ \phi^{DO} + \beta \mathbb{E}\left[V_{t+1}^{DO}(s_{t+1}, \varepsilon_{it+1}^{DO}) | s_t, \varepsilon_{it}^{DO}\right] + \varepsilon_{it}^{2,DO}, & \text{if } a_{i,t} = \text{stay} \\ \phi^{DD} + \beta \mathbb{E}\left[V_{t+1}^{DD}(s_{t+1}, \varepsilon_{it+1}^{DD}) | s_t, \varepsilon_{it}^{DO}\right] - \kappa + \varepsilon_{it}^{3,DO} & \text{if } a_{i,t} = \text{donate} \end{Bmatrix}$$

$$V_t^{DD}(s_t, \varepsilon_{it}^{DD}) = \pi_t^{DD}(s_t, \cdot) + \max_{a_{i,t} \in \mathscr{A}} \begin{Bmatrix} \varepsilon_{it}^{1,DD}, & \text{if } a_{i,t} = \text{exit} \\ \phi^{DD} + \beta \mathbb{E}\left[V_{t+1}^{DD}(s_{t+1}, \varepsilon_{it+1}^{DD}) | s_t, \varepsilon_{it}^{DD}\right] + \varepsilon_{it}^{2,DD} & \text{if } a_{i,t} = \text{stay} \end{Bmatrix}$$

New Entrants Normalizing the outside option for all entrants to 0, the problem of each one of them becomes $\max\{0, V_t^{\cdot}(s_t) - \kappa^{ent}\}$, which by free entry condition implies that $V_t^{\cdot}(s_t) \leq \kappa^{ent}$.

Equilibrium We analyze the finite-horizon, sequential-move dynamic discrete-choice game with private information by characterizing its Perfect Bayesian Equilibrium in type-symmetric pure strategies. Two modeling assumptions ensure equilibrium uniqueness and computation via backward induction. First, private information consists of i.i.d cost shocks of firms' discrete choices rather than firm heterogeneity. As a result, payoffs depends on rivals' shocks only through their observed choices.[31] Second, firms move sequentially, fully informed about the earlier movers' actions. Thus, a firm faces a single-agent decision conditioned on anticipated market dynamics. We start the backward induction by assuming that the terminal values associated with firm states are given by:

$$\left(V_T^{OO}, V_T^{OD}, V_T^{DO}, V_T^{DD}\right) = \left(\sum_{t=T}^{\infty} \beta^t \pi_T^{OO}(s_T), \sum_{t=T}^{\infty} \beta^t \pi_T^{OD}(s_T), \sum_{t=T}^{\infty} \beta^t \pi_T^{DO}(s_T), \sum_{t=T}^{\infty} \beta^t \pi_T^{DD}(s_T)\right)$$

In $T-1$, non-yet-donor firms of the second electoral cycle $(N_{T-1}^{OO}, N_{T-1}^{DO})$, choose the action that maximizes their continuation value in the last period:

$$\max\left\{\varepsilon_{i,T-1}^{1,OO},\ \phi^{OO} + \beta \mathbb{E}\left[V_T^{OO}(s_T) \mid s_{T-1}\right] + \varepsilon_{i,T-1}^{2,OO},\ \phi^{OD} + \beta \mathbb{E}\left[V_T^{OD}(s_T) \mid s_{T-1}\right] - \kappa + \varepsilon_{i,T-1}^{3,OO}\right\}$$

$$\max\left\{\varepsilon_{i,T-1}^{1,DO},\ \phi^{DO} + \beta \mathbb{E}\left[V_T^{DO}(s_T) \mid s_{T-1}\right] + \varepsilon_{i,T-1}^{2,DO},\ \phi^{DD} + \beta \mathbb{E}\left[V_T^{DD}(s_T) \mid s_{T-1}\right] - \kappa + \varepsilon_{i,T-1}^{3,DO}\right\}$$

Donor firms of the second electoral cycle $(N_{T-1}^{OD}, N_{T-1}^{DD})$ choose the action that solves:

$$\max\left\{\varepsilon_{i,T-1}^{1,OD},\ \phi^{OD} + \beta \mathbb{E}\left[V_T^{OD}(s_T) \mid s_{T-1}\right] + \varepsilon_{i,T-1}^{2,OD}\right\}$$

$$\max\left\{\varepsilon_{i,T-1}^{1,DD},\ \phi^{DD} + \beta \mathbb{E}\left[V_T^{DD}(s_T) \mid s_{T-1}\right] + \varepsilon_{i,T-1}^{2,DD}\right\}$$

[31] Our equilibrium follows the Perfect Bayesian Equilibrium (PBE) concept, but the results are equally valid under Sequential Equilibrium (SE). The distinction lies in the treatment of off-path beliefs. SE imposes additional consistency requirements relative to PBE. However, in our setting, private information enters only through i.i.d. cost shocks that affect payoffs via firms' actions. As a result, off-path beliefs about these shocks do not influence equilibrium behavior. This implies that our equilibrium satisfies the belief consistency conditions required by SE.

To compute the value functions $V^{\cdot\cdot}_{T-2}$ in $T-2$, we derive an expression for the conditional expected value before observing the shocks $\varepsilon_{i,t}$. We follow Rust (1987) and Igami (2018) intuition exploiting the properties of the i.i.d logit errors to obtain closed-form expressions as follows:

$$\mathbb{E}_{\varepsilon_{i,T-1}}\left[V^{OO}_{T-1}(s_{T-1},\varepsilon_{i,T-1}) \mid s_{T-1}\right] = \pi^{OO}_{T-1}(s_{T-1}) + \rho\left\{\gamma + \ln\left[\exp(0) + \exp\left(\frac{\phi^{OO} + \beta\mathbb{E}[V^{OO}_{T}(s_T) \mid s_{T-1}]}{\rho}\right) + \exp\left(\frac{\phi^{OD} + \beta\mathbb{E}[V^{OD}_{T}(s_T) \mid s_{T-1}] - \kappa}{\rho}\right)\right]\right\}$$

$$\mathbb{E}_{\varepsilon_{i,T-1}}\left[V^{OD}_{T-1}(s_{T-1},\varepsilon_{i,T-1}) \mid s_{T-1}\right] = \pi^{OD}_{T-1}(s_{T-1}) + \rho\left\{\gamma + \ln\left[\exp(0) + \exp\left(\frac{\phi^{OD} + \beta\mathbb{E}[V^{OD}_{T}(s_T) \mid s_{T-1}]}{\rho}\right)\right]\right\}$$

, where γ is the Euler constant. Expected value functions of firms in state $s_{i,t} = DO$ and $s_{i,t} = DD$ are equivalent (see Appendix C.1.1). The expressions allow us to recursively construct the sequence of expected value functions for all periods. The policy functions implied by this process characterize the choice probabilities that underpin the maximum likelihood estimation detailed below.

6.2 Estimation and Identification

Since procurement is decentralized, we consider each municipality as an independent market. We decrease the contractor space by municipality aggregating units in representative agents based on unit type (firm or individual), donation status, and entry patterns. This allow us to aggregate the data while keeping the structure of the relevant features that the model intends to capture. The estimation proceeds in three steps. First, we estimate the public sector demand for contracts using the intervention of Section 5 as an exogenous demand shifter, and recover marginal costs from first-order conditions. Second, we compute the firms' per-period profit conditional on any market structure s_t using the estimated demand and marginal cost. Finally, we embed the per-period profits into the dynamic discrete game to estimate the sunk cost of donating κ, entering κ^{ent}, and the state-specific fixed costs/fringe benefits ϕ^{OO}, ϕ^{DO}, ϕ^{OD}, ϕ^{DD}.

Demand We model the mayor's choice among discretionary contract types as a multinomial discrete choice. Each contract type j is defined at the municipality–contractor type (firm or individual)–donation status–sector level. Donation status is therefore embedded in the definition of j, and any systematic preference for donor relative to non-donor alternatives is captured by a type specific component γ_j and an unobserved component ξ_{jt}. The indirect utility associated with awarding contract type j in period t is then given by

$$U_{jt} = \gamma_j + \eta_t + \beta' x_{jt} + \alpha\, p_{jt} + \xi_{jt} + \varepsilon_{jt}, \tag{3}$$

where γ_j and η_t denote contract-type and time specific components, x_{jt} collects observed time-varying characteristics, and ε_{jt} follows the type 1 extreme value distribution. The term p_{jt} denotes the effective price internalized by the mayor. The data record only its monetary component (the contract value),

while the effective price may also include an unobserved political or oversight cost associated with awarding contracts of type j. The coefficient α measures the marginal utility cost of this effective price. The term ξ_{jt} captures unobserved time-varying characteristics such as quality, complexity, etc. Open-tender contracts serve as the outside option with mean utility normalized to zero.

Favoritism toward donors is reflected in the mean utility $(\gamma_j + \xi_{jt})$ of donor types relative to comparable non-donor types. Let ms_{jt} denote the market share of contract type j and ms_{0t} the share of the outside option. Under the multinomial logit structure implied by (3),

$$ms_{jt} = \frac{\exp\left(\gamma_j + \eta_t + \beta' x_{jt} + \alpha\, p_{jt} + \xi_{jt}\right)}{1 + \sum_l \exp(\gamma_l + \eta_t + \beta' x_{lt} + \alpha\, p_{lt} + \xi_{lt})}. \tag{4}$$

Following Berry (1994), the market share equation admits the inversion

$$\ln\left(\frac{ms_{jt}}{ms_{0t}}\right) = \gamma_j + \eta_t + \beta' x_{jt} + \alpha\, p_{jt} + \xi_{jt}. \tag{5}$$

The parameters (β, α) characterize how observed attributes and the effective price shape mayoral choices. Since ξ_{jt} is observed by mayors but not by the econometrician, it may be correlated with the effective price p_{jt}. The observed monetary component of the price therefore reflects both underlying scarcity and the unobserved oversight cost, rendering p_{jt} endogenous in (5).

The randomized assignment in Section 5 provides a source of exogenous variation in the effective price of donor contract types. The letters increase the oversight cost faced by mayors when allocating donor contracts, thereby shifting the effective price in treated municipalities while remaining orthogonal to ξ_{jt}. These shocks propagate to the observed monetary component of price through equilibrium adjustments in procurement markets. Using the treatment indicators as instruments for p_{jt} identifies the causal effect of the effective price on demand, summarized by α, and permits a structural interpretation of how increased oversight reduces the allocation of contracts to donors.

Market Competition and Marginal Costs We model our setting as a market in Cournot competition with heterogeneous marginal costs based on firms' state, motivated by three features. First, public contracts typically involve standardized goods or services, leading firms to compete primarily on quantities and contract terms. Second, firms' are constrained by slow to adjust fixed resources and sunk investments, so competition is driven by available capacities. Third, firms–particularly donors–perceive positive returns, suggesting a strategic advantage linked to their status.[32]

[32]Although the government often acts as the sole purchaser in procurement, supplier behavior cannot be reduced to a monopsony model. In practice, local procurement in Colombia is discretionary, not organized through formal auctions, and contracts are typically distributed among several firms subject to budgetary and capacity constraints. In this environment, Cournot competition provides a more accurate description: firms choose output levels given their costs, and prices emerge endogenously from the aggregation of these supply decisions. Each supplier recognizes that expanding its own output reduces the residual demand faced by rivals and depresses the effective price. Entry restrictions, and binding capacity limits further reinforce this structure, ensuring that allocations and prices are determined not only by a dominant public buyer but

The marginal costs for firms in each state are assumed constant with respect to quantity and uniform within state in t. Firms maximize profits $\pi_{it} = (P_t - mc_{it})q_{it}$, with q_{it} equal to the firm's offered quantity, P_t the average contract price in a municipality, and mc_{it} the firm's state-specific marginal cost. The first-order condition that allow us to infer the marginal costs in each period is

$$P_t + \frac{\partial P_t}{\partial Q_t} q_{it} = mc_{it}$$

with $Q_t = \sum_i q_{it}$ equal to the total market quantity observed from the data. $\partial P_t / \partial Q_t$ is recovered from estimating equation 5, and our data allow us to calculate P_t and q_{it}.[33]

We extend the baseline framework by introducing a simple modification to the Cournot structure that captures additional competitive advantages from donating. In the standard model, donor firms compete against all active firms in the market. Since donors are a small fraction of participants, this would imply a low survival probability for donors, which is at odds with the empirical evidence that donations are associated with persistent access to procurement. To reconcile this, and based on anecdotal evidence, we posit that donating moves firms into a smaller, more exclusive competitive pool in which they compete only with other donors at a given point in time. Formally, we adjust the first-order condition as:

$$P_t + \theta_s \frac{\partial P_t}{\partial Q_t} q_{it} = mc^s_{it} \tag{6}$$

where θ_s is a competition intensity multiplier. $\theta_s = 1$ reproduces the standard Cournot conditions, while $\theta_s < 1$ captures thinner competition. We allow firms in "donor" states to face $\theta_s < 1$ and parameterize $\theta = \sigma(\gamma_0 + \gamma_1 \times t + \gamma_2 \times \frac{N^{OD}+N^{DD}}{N})$ so that competition intensity varies smoothly with the share of firms in donor states. In 6, $\sigma(\cdot)$ denotes a logistic function ensuring $\theta_s \in (0, 1]$. Appendix C.2 provides a potential micro-foundation for this extension. Importantly, this modification does not alter the timing, state space, or estimation procedure of the model. We recover θ_s by calibrating the parameters γ to maximize the log-likelihood described below.

Likelihood Using the demand parameters and marginal costs we compute per-period profits for each firm type in period t conditional on market structure s_t. Then, we integrate the profits into the dynamic discrete-choice game and solve it via backward induction using Maximum Likelihood Estimation. We fix β and δ to constant values and conduct sensitivity analysis.[34]

We construct the likelihood of observing firms' actions allowing δ to scale the sunk cost of

also by the rivalry among a limited set of regional contractors.

[33] Because we aggregate our data at the municipality-contract type level, we impose symmetry across firms of the same donation status as an identifying assumption.

[34] The discount factor β is not estimated due to the now very well documented identification challenges (Rust, 1987). Similarly, while a parameter for the rate of change in sunk costs, δ, could enhance the model's fit to donation timing, its estimation is computationally intensive. We fix baseline $\beta = 0.8$ and $\delta = 0.95$.

donating over time ($\delta^t \kappa$). The likelihood contribution of firm i in period t, given its state s_{it} and action a_{it}, is derived from the choice probabilities implied by the type-symmetric Perfect Bayesian Equilibrium. These probabilities reflect firms' dynamic decisions, conditional on the market structure s_t and idiosyncratic cost shocks ε_{it} (i.i.d. type-1 extreme value with scale parameter ρ). The contribution of an incumbent firm i in year t to the likelihood when such it is at state $s_{i,t} = OO$ is:

$$\begin{aligned} f^{OO}(a_{i,t}|s_t;\phi^{OO},\phi^{OD},\kappa,\rho) = &\Pr(a_{i,t}=\text{exit})^{\mathbb{1}(a_{i,t}=\text{exit})} \times \Pr(a_{i,t}=\text{stay})^{\mathbb{1}(a_{i,t}=\text{stay})} \\ &\times \Pr(a_{i,t}=\text{stay, donate})^{\mathbb{1}(a_{i,t}=\text{stay, donate})} \end{aligned}$$

The probabilities of each action are given by:

$$\Pr(a_{it}=\text{exit}) = \frac{1}{1 + \exp\Big(\frac{\phi^{OO} + \beta E_\varepsilon V_{t+1}^{OO}(s_{t+1})}{\rho}\Big) + \exp\Big(\frac{\phi^{OD} + \beta E_\varepsilon V_{t+1}^{OD}(s_{t+1}) - \delta^t \kappa}{\rho}\Big)}$$

$$\Pr(a_{it}=\text{stay}) = \frac{\exp\Big(\frac{\phi^{OO} + \beta E_\varepsilon V_{t+1}^{OO}(s_{t+1})}{\rho}\Big)}{1 + \exp\Big(\frac{\phi^{OO} + \beta E_\varepsilon V_{t+1}^{OO}(s_{t+1})}{\rho}\Big) + \exp\Big(\frac{\phi^{OD} + \beta E_\varepsilon V_{t+1}^{OD}(s_{t+1}) - \delta^t \kappa}{\rho}\Big)}$$

$$\Pr(a_{it}=\text{stay, donate}) = \frac{\exp\Big(\frac{\phi + \beta E_\varepsilon V_{t+1}^{OD}(s_{t+1}) - \delta^t \kappa}{\rho}\Big)}{1 + \exp\Big(\frac{\phi^{OO} + \beta E_\varepsilon V_{t+1}^{OO}(s_{t+1})}{\rho}\Big) + \exp\Big(\frac{\phi^{OD} + \beta E_\varepsilon V_{t+1}^{OD}(s_{t+1}) - \delta^t \kappa}{\rho}\Big)}$$

The contribution of an incumbent firm i in year t to the likelihood when it is at state $s_{i,t} = OD$ is

$$g^{OD}(a_{i,t}|s_t;\phi^{OD},\rho) = \Pr(a_{i,t}=\text{exit})^{\mathbb{1}(a_{i,t}=\text{exit})} \times \Pr(a_{i,t}=\text{stay})^{\mathbb{1}(a_{i,t}=\text{stay})}$$

The probabilities of each action are given by:

$$\Pr(a_{it}=\text{exit}) = \frac{1}{1 + \exp\Big(\frac{\phi^{OD} + \beta E_\varepsilon V_{t+1}^{OD}(s_{t+1})}{\rho}\Big)}$$

$$\Pr(a_{it}=\text{stay}) = \frac{\exp\Big(\frac{\phi^{OD} + \beta E_\varepsilon V_{t+1}^{OD}(s_{t+1})}{\rho}\Big)}{1 + \exp\Big(\frac{\phi^{OD} + \beta E_\varepsilon V_{t+1}^{OD}(s_{t+1})}{\rho}\Big)}$$

Firms in states $s_{i,t} = DO$, $f^{DO}(a_{i,t}|s_t;\phi^{DO},\phi^{DD},\kappa,\rho)$ and $s_{i,t} = DD$, $g^{DD}(a_{i,t}|s_t;\phi^{DD},\kappa,\rho)$ likelihood contributions have a similar form (see Appendix C.1.2). The overall likelihood for the observed

sequence of firm actions across all periods is given by:

$$L(\omega) = \prod_{t=0}^{T-1} \left[\prod_{s \in \{\text{OO,DO}\}} \prod_{i \in I_t^s} f^s(a_{i,t} \mid s_t; \omega) \times \prod_{s \in \{\text{OD,DD}\}} \prod_{i \in I_t^s} g^s(a_{i,t} \mid s_t; \omega) \right] \tag{7}$$

where $\omega = (\phi^{\text{OO}}, \phi^{\text{OD}}, \phi^{\text{DO}}, \phi^{\text{DD}}, \kappa, \rho)$ is the vector of parameters to be estimated. I_t^s denotes the set of incumbent firms in state s in period t. The estimated dynamic parameters are obtained by maximizing the log-likelihood $\hat{\omega} = \arg\max_\omega \ln L(\omega)$.

We compute the choice probabilities $f^s(a \mid s_t; \omega), g^s(a \mid s_t; \omega)$ solving the dynamic game by backward induction for each candidate parameter vector ω using the per-period profits (π_t^{OO}, π_t^{OD}, π_t^{DO}, π_t^{DD}). The entry costs κ_t^{ent} are inferred using the *free-entry condition*: in equilibrium, firms enter the market until the expected value of entry equals the cost for the marginal entrant. This is achieved by defining $\kappa_t^{\text{ent}} = V_t^{\cdot}(s_t)$ with $V_t^{\cdot}(s_t)$ indicating the expected present value of future profits for an entrant given s_t. This allow us to ensure that the predicted entry behavior aligns with the data allowing the likelihood to focus on incumbent firms' decisions.

To clarify our identification, we highlight the sources of variation that separately discipline each block of the model. The demand parameters are identified from cross-municipality and over-time variation in contract attributes, combined with the randomized intervention in Section 5 which provides exogenous shifts in effective prices. The marginal costs and competitive structure are identified from the first-order conditions that link observed quantities and prices to the slope of the residual demand curve. The dynamic parameters are identified from firms' transition patterns across states and actions, conditional on per-period profits recovered in the first two stages. Taken together, these sources of variation ensure separate and coherent identification of demand, costs, and the dynamic incentives that govern donation and exit decisions.

6.3 Structural Model Results

Demand and Marginal Cost We estimate demand using equation 5, regressing the log market share of discretionary contracts on the average contract value (price), with municipality, sector and year fixed effects so that variation comes from firms in the same type of contract across municipalities over time. We exploit the randomized treatment in Section 5 as a demand shifter to recover exogenous variation in prices. Specifically, we instrumenting the price with the interaction between the treatment assignment and a dummy variable equal to one for the year 2024 (when the treatment shock occurred) for donor and non-donor firms, so they are compared relative to firms in the control group.

Table 3 presents the OLS and 2SLS demand estimates, all of which are negative and statistically significant. Our preferred specification in column (3) indicates that a one million COP increase in contract prices (driven by municipalities being exposed to more monitoring and oversight) reduces the market share of discretionary contracts in 54% relative to non-discretionary contracts. Column

(4) allows for price heterogeneous effects, and shows that government sector jobs have a differential additional response to price increases. This is expected as those are the type of contracts for which mayors hold more discretionary power, but also those for which increased prices can push contracts to be above discretionary thresholds, thus limiting discretionary capacity. Notably, the semi-elasticity for non-government services is still negative and significant. We use the column (3) estimate as the demand parameter.

Table 3: Demand for public contracts estimates

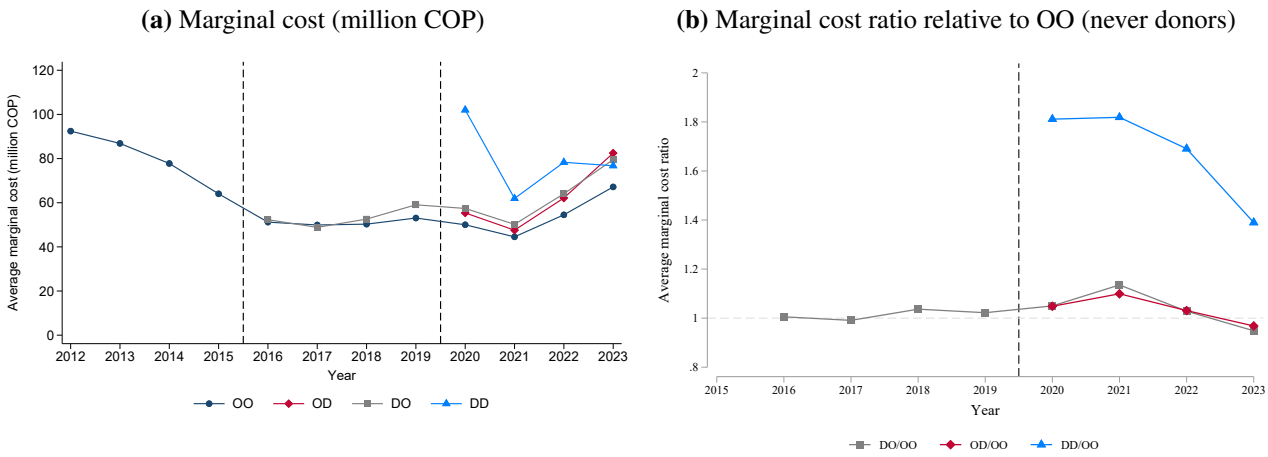
Dep. Variable	Log(share of contracts)			
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
P (million COP)	-0.016***	-0.011***	-0.539***	-0.314**
	(0.001)	(0.001)	(0.045)	(0.124)
P (million COP) $\times \mathbb{1}$[Sector = Gov. Services]		-0.052***		-0.490*
		(0.003)		(0.276)
N. of obs.	58,250	58,250	58,250	58,250
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
First Stage F-Statistic			50.992	4.114

Notes: The unit of analysis is the municipality-donation status-sector-year, estimating a linear regression using as outcome the log market shares of discretionary contracts and as explanatory variable the price –average contract value– weighted by the number of contractors represented by each cell municipality-donation status-sector. All columns include fixed effects by municipality, sector, and year. Column (2) and (4) allow the price to vary by sector by estimating as an additional endogenous regressor the interaction of price with the cells corresponding to contracts coded as government services. Column (3) and (4) use as instrument the treatment assignment from the RCT described in section 5, interacted with a dummy for the year 2024 (period when the RCT was implemented), and a dummy for donation status. We aggregate all RCT arms into a single treatment, so that we estimate an interaction for donors and non-donors relative to the control group. The F-stat corresponds to the first stage Kleibergen-Paap statistic. Standard errors clustered at the municipality level in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, we solve the Cournot first-order conditions (equation 6) to compute marginal costs for firms across donor states. Panel (a) of Figure 12 reports the marginal costs, and Panel (b) plots ratios relative to never-donors. One time donors (DO, OD) have a marginal costs similar to never donors, with their ratio rising slightly after the 2023 elections. Although these gaps appear modest, administrative evidence suggests that small differences can influence firms' participation decisions, particularly in public procurement where margins are narrow. The patterns indicate a convergence in cost structures, possibly reflecting learning, economies of scale, or the normalization of donation behavior. In contrast, repeat donors (DD) display the highest marginal cost and a substantial percentage increase relative to non-donors. These elevated costs are consistent with the limited overlap of donors across electoral cycles, as donating twice likely signals a worse underlying type.

Cost of Donation and Fringe Benefits of Operation We estimate the structural model in the 428 municipalities that exhibit sufficient variation in firms' donor states and procurement participation,

Figure 12: Implied marginal cost estimates by state



Note: The figure reports in Panel (a) the level of implied marginal cost in million COP by transition state. Panel (b) show the ratio between the implied marginal cost of adopters relative to the implied marginal cost of never adopters. The marginal cost is calculated using data on prices, quantity shares and the estimated demand parameter, based on data aggregated at the municipality-by-representative agent-by-year.

ensuring that transitions into donation and entry/exit decisions are empirically observable. [35] Panel (a) of Figure 13 plots municipal distribution of the (log) κ, the sunk cost of becoming a donor, and compares it with the observed average donated value by municipality. While the two distributions overlap, the estimated sunk cost frequently exceeds reported donation levels –on average, the sunk cost exceed donated values in 84%. This discrepancy likely reflects unobserved costs not captured by donation records and suggests that donors face additional hidden costs when deciding to contribute to a political campaign.[36]

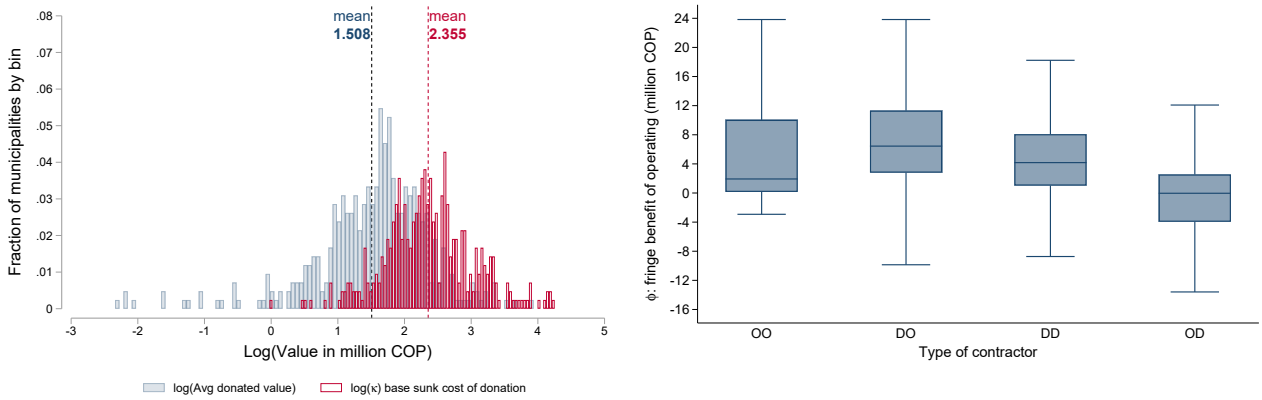
Panel (b) of Figure 13 reports the estimated state-dependent operating cost (or benefit) ϕ. Positive values indicate fringe benefits, meaning that participating in procurement typically offsets fixed operating costs and yields net gains. The distributions for non-donor states (*OO*, *DO*) are similar and generally positive, while donor states, in particular *OD* state, tend toward negative values. These differences are large and informative for understanding firms' choices. Consistent with a pay-to-play dynamic, firms in state *DO* –not donors but donated before– enjoy significant benefits from participating in public procurement.

[35]The demand parameter is estimated using the full set of 876 municipalities included in the randomized controlled trial (Section 5). However, the structural model requires empirical variation in firms' state transitions for the likelihood to be well-defined. Municipalities with no donor states, donation (*DO*, *OD*) or with negligible entry and exit in procurement for states (*OO*, *DO*, *OD*) generate deterministic choice patterns. In such cases, the likelihood assigns degenerate probabilities, leading to non-identified or unbounded parameters (e.g., infinite costs). The 428 municipalities used in estimation are precisely those where all relevant transitions occur at least once, allowing the model to recover finite and economically meaningful parameters.

[36]Importantly, κ is not designed to track donation magnitude directly. Instead, the model's discrete-choice structure and free-entry condition ($\kappa^{ent} = V_t^{\cdot}(s_t)$) ensure that κ rationalize observed transitions into donation states, rather than to replicate observed donation levels or costs.

Figure 13: Distribution of model estimated parameters

(a) Sunk cost of donation κ **(b)** Fringe benefits ϕ by state



Note: The figure plots in Panel (a) the municipal distribution of the (log-transformed) structural parameter κ for the sunk cost of donation and the municipal average donation value. Panel (b) report the distribution of the fringe benefit/cost of operation by transition state. Outside values no shown. Estimated parameters are obtain through MLE. The parameters were obtained using $\beta = 0.8$ and $\delta = 0.95$.

Overall, the structural parameters highlight the central role of economic conditions in shaping firms' incentives to donate and participate in public procurement. The estimates suggest that firms face significant hidden costs of donating in addition to the amounts reported in campaign records. Moreover, the fixed cost parameters indicate that not donating in the current period but having donated before yields larger net benefits than donating twice or donating only in the current period. This pattern implies that donors face meaningful entry barriers relative to firms in other states, consistent with donation serving as a costly signal to secure long-term access.[37]

What are the Sunk Costs of Donating? [Preliminary - To be Completed] To shed light on what the hidden costs κ capture, we correlate the estimated parameter with municipal characteristics that plausibly shape firms' incentives to donate. Figure C2 shows that municipalities with more concentrated procurement markets (higher HHI) exhibit lower sunk costs. One interpretation is that donors can more easily secure privileged access when competition is limited to a smaller set of contractors. Alternatively, highly concentrated procurement may reflect entrenched corruption (Deryugina et al., 2025), in which case accessing preferential treatment is easier and therefore less costly.

We also find that municipalities with greater fiscal capacity (higher local tax collection and larger national transfers) display higher sunk costs. This pattern suggests that access becomes more expensive in places where procurement budgets are larger and competition for contracts is more intense. Sunk costs are further positively associated with local violence and the presence of illegal armed groups. In

[37] Figure C1 in the Appendix show that the implied entry decision from the estimated model follow the patterns in the data. As such, our model correctly map the transition probabilities leading to entry, exit, and donation decision.

such contexts, firms may need to navigate multiple political or criminal actors to secure preferential treatment, each potentially requiring compensation, thereby increasing the overall cost of donating.

Together, these correlations provide suggestive evidence that the hidden costs of donating reflect institutional and political frictions that vary systematically across municipalities.

Return on Investment of Political Contributions The model show that the economic incentives driving firms' decisions to donate and participate in public procurement are sizable. But how do these reconcile with the small scale of political contributions? We revisit Tullock's puzzle (Tullock, 1972; Ansolabehere, De Figueiredo and Snyder Jr, 2003) by computing the returns on investment of donating once hidden costs are taken into account.

Specifically, we compute the return on investment using the estimated sunk cost of donating as the initial value, and define annual cash flows as the sum of contract values and the estimated fringe benefits (or costs) associated with each donor type. We then compare these to those obtained using only observed data. Figure 14 shows that when using only observed data and implied marginal costs, the median return reaches 102%, driven by a long right tail. The distribution is bimodal, with one peak around zero or small returns and another near 100%. This suggests that, absent hidden costs, donating appears profitable for a relatively narrow group of donors with large profit margins.

Once hidden costs are incorporated (red distribution), the median return falls to roughly 47%, and the entire distribution compresses to the left. While returns may still be sizable, accounting for hidden costs substantially increases the mass of firms with returns close to or below zero, raising the likelihood of losses when deciding to donate. Panel (b) plots the difference between the two rates. For most contractors, the difference is positive, meaning that their perceived return declines markedly once hidden costs are included.

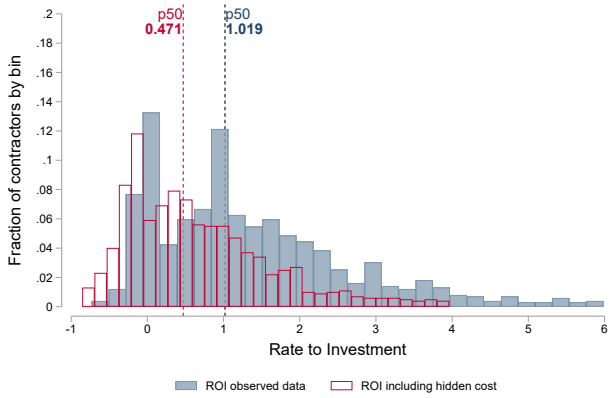
Taken together, these findings offer a novel explanation for why, despite large observed returns, there is little money in politics, as firms' hidden costs significantly reduce the returns to donating and participate in public procurement

Counterfactual Policies and Welfare **[Preliminary - To Be Completed]** We proceed to use our results to estimate counterfactual policies usually implemented to reduce distortions from political donations, and calculate their welfare consequences. First, we evaluate a full contract ban assuming a prohibitively high sunk cost ($\kappa \times 5$). Second, we test for an increase in donation limits, considering that if firms are allowed to donate more, the sunk cost decreases. We implement the policy reducing κ to $\frac{\kappa}{5}$. Third, we propose a cooling down policy, in which donors are not allowed immediate entry to the procurement system, but only two years after donating. The policy forces donors to pay the sunk costs of donation, but forbid them to receive the profits from contract allocation, and fringe benefits of operations, if any.

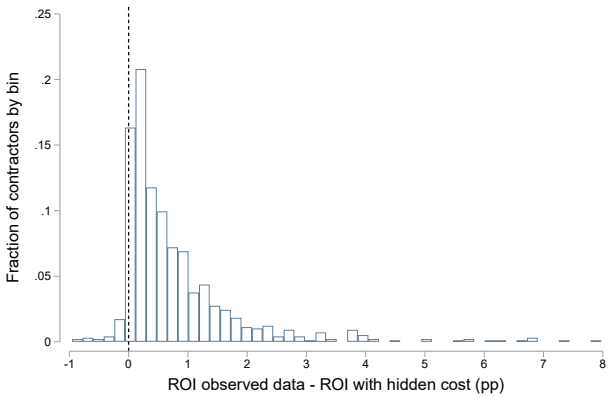
Figure C3 in the Appendix show that the implied adopter entries from a full ban and increased

Figure 14: Return on Investment of Donating

(a) Return on Investment distribution



(b) Difference in returns on investment



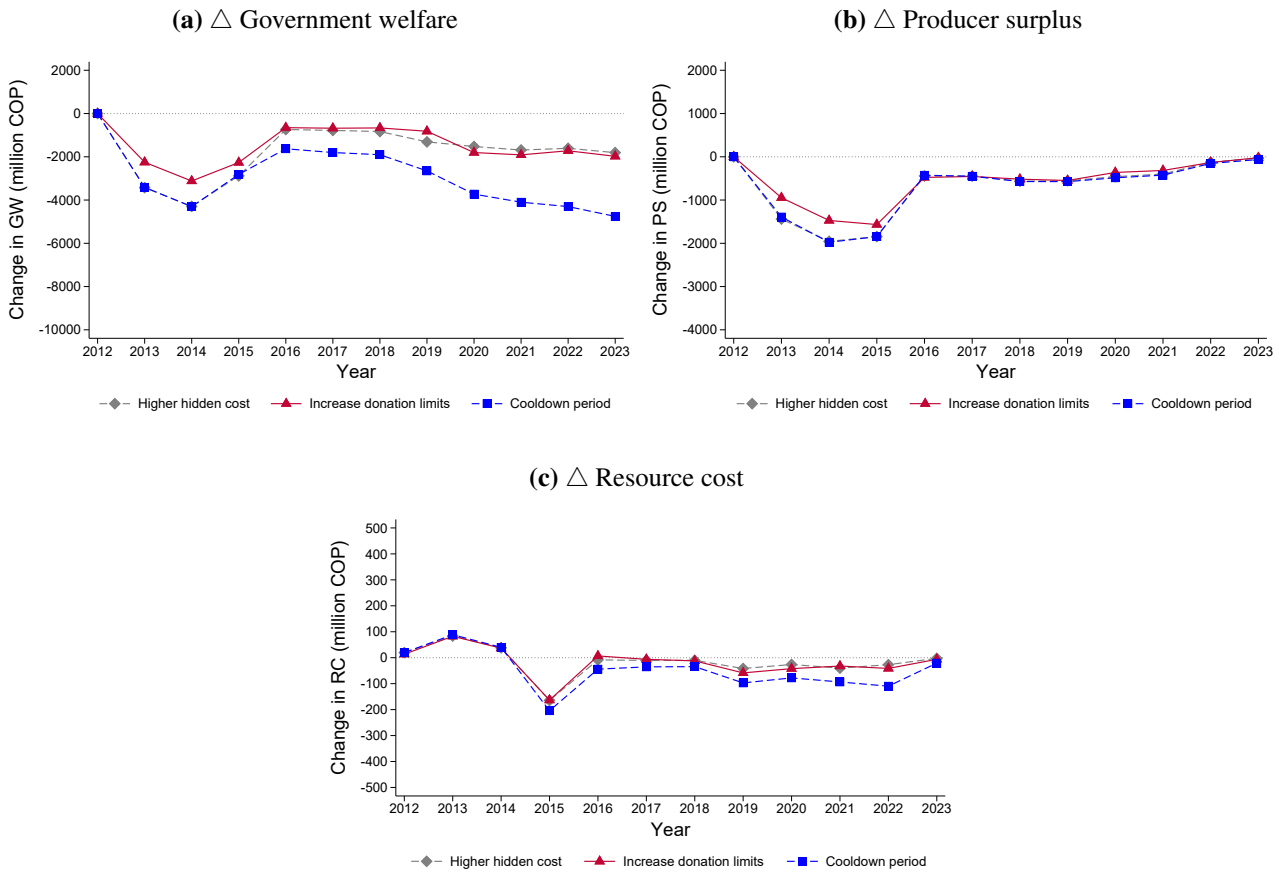
Note: The figure plots the distribution of donors return on investment based on the observed data (blue) and including the estimated parameters (red). Both distributions also include the marginal cost recovered from the Cournot first-order conditions. We calculate the return on investment using the present value of all the cashflows after the donation. At time $t = 0$, agents incur in a cost of donating (observed or sunk cost). For $t > 0$, each period benefit is the total contracted value plus the fringe benefits when including the hidden parameters. The cost includes the marginal cost of the contract and the fringe cost of operating in the procurement system. Red and blue horizontal lines indicate the median of the return on investment distribution with and without accounting for the hidden costs, respectively. Panel (b) plots the distribution of the difference between the two rates by contractor.

donation threshold deviates very little from the base model, suggesting that adopters are not highly sensible to the cost of donation. If the cost is high, donors might still perceive benefits from positive fringe benefits, or advantages in contract assignment. As such, donors are willing to pay more for receiving privileged access. On the contrary, the cooldown policy shows a decrease in the number of adopters, as it targets donors profits directly instead of hidden costs.

Next, we assess the welfare effects of the counterfactual policies. We compute (i) government welfare, defined as the mayor's procurement utility net of expenditures, (ii) producer surplus, measured as the sum of firms' equilibrium profits across types, and (iii) resource costs, defined as the real resource expenditures associated with donating, entry, and operation (see Appendix C.3 for details). Figure 15 compares each counterfactual outcome to the baseline welfare level. Panels (a) and (b) show that none of the policies increase government or firm welfare. A plausible interpretation is that although the policies reduce favoritism, they also induce the exit of high-performing donors and lead to large entry of less productive non-donors, raising government spending and lowering firms' profits. Panel (c) shows no reduction in resource costs, implying that, on top of lower profits, firms also face higher operating costs.

[To Be Completed]

Figure 15: Welfare Change Relative to Baseline



Note: The figure plots the entries for agents donating from the base model (blue) and counterfactual policies (red). Panel (a) show the result from a policy banning the entry to the procurement system to donors. The policy is implemented by estimating the model using the optimal parameters and replacing κ by $\kappa \times 5$. Panel (b) show the results for decreasing the sunk cost of donation (allowing more legal donations). The policy is implemented by estimating the model using the optimal parameters and replacing κ by $\frac{\kappa}{5}$. Panel (c) implements a cooldown policy, consisting in forbidding the entry to the procurement system to donors during two years after adoption. The policy is implemented by estimating the optimal model including a constrain in which donors are not allowed to entry until two periods after adoption.

7 Conclusion

Our findings show that campaign contributions in Colombian municipal procurement function as a lasting market-access fee rather than as isolated quid pro quo exchanges. Donor firms bear hidden costs, higher implied marginal costs relative to non-donors, lower fixed benefits of operation, and administrative and reputational burdens. Despite these disadvantages, donating unlocks a privileged lane. Donors secure a disproportionate share of discretion-based contracts, cluster their awards just below thresholds that would trigger open tenders, and continue to win long after their preferred politicians leave office. Our dynamic model based on forward-looking firms rationalizes these patterns. Once a firm donates for the first time, the marginal cost disadvantage is reduced. In the long run,

donors operate at cost parity with non-donors while still capturing political rents.

Results from our nationwide randomized experiment confirm that the pay-to-play equilibrium depends on selective enforcement rather than on economic fundamentals alone. When newly elected mayors are told that the Inspector General will monitor their donors and receive an attached list of donor identities, favoritism declines and remains low for up to a year, which is the period we study. Treatment arms that rely only on journalistic exposure or generic warnings produce no comparable change. This pattern shows that actionable information must be paired with credible sanctions. Integrating these insights with our structural estimates illustrates how modest frictions at the donation and entry margins, combined with weak oversight, can steer a procurement market toward connected insiders. Effective policies therefore require lowering informational and bureaucratic barriers for non-donors while raising the probability of punishment for favoritism. These steps are essential for restoring competition, efficiency, and accountability in settings where state capacity is limited.

We study whether political campaign donations serve as a form of pay-to-play in public procurement, generating long-term distortions in the allocation of public contracts. Our results draw on a comprehensive dataset linking donations to mayoral campaigns with the universe of public procurement contracts in Colombia. We find that donors receive more and higher-valued contracts immediately after an election. They also continue to secure public contracts in later administrations after the political connection has lapsed. The persistent effect suggests that donations provide long-term insider status rather than short-term reciprocity from the winning politician. The reduced-form evidence also indicates that donors often display weaker ex ante performance, are more likely to manipulate procurement processes, and incur higher cost overruns relative to non-donors. Together, these behaviors underscore the efficiency and resource-allocation costs associated with pay-to-play dynamics, since donors can extract rents through added discretion.

We implemented a large-scale nationwide randomized controlled trial to counteract distortions produced by political campaign donors. In partnership with the Office of the Inspector General, investigative journalists, and anti-corruption NGOs, we sent letters to newly sworn mayors informing them about the legal risks of awarding contracts to donors. The intervention varied the identity of the oversight authority named in the letter and the degree of donor information disclosed. The findings show that monitoring can curb preferential treatment only when there is both a credible threat of punishment and actionable information about donor identities. Specifically, informing mayors that the Inspector General is copied on the communication, along with a detailed list of donors, significantly reduces the probability and value of donor contracts. In contrast, treatments without a credible enforcer or explicit donor details do not reduce favoritism. Moreover, donors who contributed in past electoral cycles and acquired insider status continue to capture substantial public contracts. Although the deterrence messages affect new donors, they do not change the behavior of entrenched contractors with prior donation histories. This pattern is consistent with a pay-to-play mechanism in which the main benefit of donating is long-run entry into and persistence in public contracting rather than a one-time

quid pro quo.

Motivated by these findings, we develop a structural model that incorporates contracting frictions, sunk donation costs, and cost differentials between donors and non-donors. By leveraging exogenous demand shifts induced by the experiment, we recover key parameters that describe the cost of donating and the cost of participating in public procurement. The model explains how high returns to donating can coexist with relatively few donors. The up-front monetary and hidden costs of donating are prohibitively large despite the permanent benefits perceived by firms once they become donors.

Two sets of policy lessons follow. First, oversight approaches are most effective when the monitoring agent has the authority to impose sanctions and has actionable information about donor identities. This highlights the role of targeted transparency in limiting corruption in procurement. Second, pay-to-play can arise from persistent distortions linked to the cost of entry into the procurement system for donors. Policies aimed only at reducing immediate quid pro quo behavior will have limited impact unless they also disrupt longer-run persistence.

Overall, this paper shows that favoritism in procurement through campaign contributions is substantial and persistent, with clear evidence of allocative inefficiencies. Nonetheless, relatively low-cost improvements in oversight, particularly by a legally empowered agency with direct information on donor identities, can curb pay-to-play for new donors.

References

Acharya, Avidit, Elliot Lipnowski, and João Ramos. 2024. "Political accountability under moral hazard." *American Journal of Political Science*.

Aggarwal, Rajesh K, Felix Meschke, and Tracy Yue Wang. 2012. "Corporate political donations: Investment or agency?" *Business and politics*, 14(1): 1–38.

Ansolabehere, Stephen, John M De Figueiredo, and James M Snyder Jr. 2003. "Why is there so little money in US politics?" *Journal of Economic perspectives*, 17(1): 105–130.

Aparicio, Diego, and Carlos F Avenancio-León. 2022. "Is banning corporate contributions enough? The dynamics of incomplete campaign finance reform." *The Journal of Law and Economics*, 65(3): 581–606.

Auriol, Emmanuelle, Stéphane Straub, and Thomas Flochel. 2016. "Public procurement and rent-seeking: the case of Paraguay." *World Development*, 77: 395–407.

Avis, Eric, Claudio Ferraz, and Frederico Finan. 2018. "Do government audits reduce corruption? Estimating the impacts of exposing corrupt politicians." *Journal of Political Economy*, 126(5): 1912–1964.

Avis, Eric, Claudio Ferraz, Frederico Finan, and Carlos Varjão. 2022. "Money and politics: The effects of campaign spending limits on political entry and competition." *American Economic Journal: Applied Economics*, 14(4): 167–199.

Baltrunaite, Audinga. 2020. "Political contributions and public procurement: evidence from Lithuania." *Journal of the European Economic Association*, 18(2): 541–582.

Baltrunaite, Audinga, Cristina Giorgiantonio, Sauro Mocetti, and Tommaso Orlando. 2021. "Discretion and supplier selection in public procurement." *The Journal of Law, Economics, and Organization*, 37(1): 134–166.

Baranek, Bruno, and Vitezslav Titl. 2020. *The cost of favoritism in public procurement.* KU Leuven, Department of Economics.

Berry, Steven T. 1994. "Estimating Discrete-Choice Models of Product Differentiation." *The RAND Journal of Economics*, 25(2): 242–262.

Bertrand, Marianne, Matilde Bombardini, and Francesco Trebbi. 2014. "Is it whom you know or what you know? An empirical assessment of the lobbying process." *American Economic Review*, 104(12): 3885–3920.

Boas, Taylor C, F Daniel Hidalgo, and Neal P Richardson. 2014. "The spoils of victory: campaign donations and government contracts in Brazil." *The Journal of Politics*, 76(2): 415–429.

Bombardini, Matilde, and Francesco Trebbi. 2011. "Votes or money? Theory and evidence from the US Congress." *Journal of Public Economics*, 95(7-8): 587–611.

Bombardini, Matilde, and Francesco Trebbi. 2020. "Empirical models of lobbying." *Annual Review of Economics*, 12: 391–413.

Bosio, Erica, Simeon Djankov, Edward Glaeser, and Andrei Shleifer. 2020. "Public Procurement in Law and Practice." *American Economic Review*, 110(11): 3615–3644.

Bosio, Erica, Simeon Djankov, Edward Glaeser, and Andrei Shleifer. 2022. "Public procurement in law and practice." *American Economic Review*, 112(4): 1091–1117.

Brugués, Felipe, Javier Brugués, and Samuele Giambra. 2024. "Political connections and misallocation of procurement contracts: Evidence from Ecuador." *Journal of Development Economics*, 170: 103296.

Cabra-Ruiz, Nicolás, Santiago Torres, Laura Wills-Otero, and Valentina Castilla-Gutiérrez. 2023. "Una caracterización histórica de los partidos políticos de Colombia: 1958-2022 (A historical characterization of Colombian political parties: 1958-2022)." *Documento CEDE*, , (36).

Calonico, Sebastian, Matias D Cattaneo, and Max H Farrell. 2020. "Optimal bandwidth choice for robust bias-corrected inference in regression discontinuity designs." *The Econometrics Journal*, 23(2): 192–210.

Carreri, Maria, and Luis Martinez. 2022. "Fiscal rules, austerity in public administration, and political accountability: Evidence from a natural experiment in Colombia." *Chicago: Becker Friedman Institute for Research in Economics*.

Chen, Jiafeng, and Jonathan Roth. 2022. "Log-like? ATEs defined with zero outcomes are (arbitrarily) scale-dependent." *arXiv preprint arXiv:2212.06080*.

Colonnelli, Emanuele, and Mounu Prem. 2022. "Corruption and firms." *The Review of Economic Studies*, 89(2): 695–732.

Colonnelli, Emanuele, Mounu Prem, and Edoardo Teso. 2020. "Patronage and Selection in Public Sector Organizations." *American Economic Review*, 110(10): 3071–99.

Coviello, Decio, Andrea Guglielmo, and Giancarlo Spagnolo. 2018. "The effect of discretion on procurement performance." *Management Science*, 64(2): 715–738.

Cuneo, Martina, Jetson Leder-Luis, and Silvia Vannutelli. 2023. "Government audits." National Bureau of Economic Research.

Dahis, Ricardo, Bernardo Ricca, and Thiago Scot. 2024. "Speed of Payment in Procurement Contracts: The Role of Political Connections." *Available at SSRN 3934021*.

Deryugina, Tatyana, Alminas Žaldokas, Anastassia Fedyk, Yuriy Gorodnichenko, James Hodson, and Ilona Sologoub. 2025. "Rating Government Procurement Markets." National Bureau of Economic Research Working Paper 34479.

Duggan, John, and César Martinelli. 2017. "The Political Economy of Dynamic Elections: Accountability, Commitment, and Responsiveness." *Journal of Economic Literature*, 55(3): 916–84.

Ferraz, Claudio, and Frederico Finan. 2008. "Exposing corrupt politicians: the effects of Brazil's publicly released audits on electoral outcomes." *The Quarterly journal of economics*, 123(2): 703–745.

Fowler, Anthony, Haritz Garro, and Jörg L Spenkuch. 2020. "Quid pro quo? corporate returns to campaign contributions." *The Journal of Politics*, 82(3): 844–858.

Gerardino, Maria Paula, Stephan Litschig, and Dina Pomeranz. 2024. "Distortion by audit: Evidence from public procurement." *American Economic Journal: Applied Economics*, 16(4): 71–108.

Grotteria, Marco. 2024. "Follow the money." *Review of Economic Studies*, 91(2): 1122–1161.

Gulzar, Saad, Miguel Purroy, and Nelson A Ruiz. 2022. "Money in Politics and Kickbacks: Evidence from Colombia." *APSA Proposal*.

Gulzar, Saad, Miguel R Rueda, and Nelson A Ruiz. 2022. "Do campaign contribution limits curb the influence of money in politics?" *American Journal of Political Science*, 66(4): 932–946.

Hirsch, Alexander V, Karam Kang, B Pablo Montagnes, and Hye Young You. 2023. "Lobbyists as gatekeepers: Theory and evidence." *The Journal of Politics*, 85(2): 731–748.

Hjort, Jonas, Diana Moreira, Gautam Rao, and Juan Francisco Santini. 2021. "How research affects policy: Experimental evidence from 2,150 brazilian municipalities." *American Economic Review*, 111(5): 1442–1480.

Huneeus, Federico, and In Song Kim. 2018. "The effects of firms' lobbying on resource misallocation."

IDEA. 2014. *Funding of Political Parties and Election Campaigns: A Handbook on Political Finance.* International Institute for Democracy and Electoral Assistance.

Igami, Mitsuru. 2018. "Industry Dynamics of Offshoring: The Case of Hard Disk Drives." *American Economic Journal: Microeconomics*, 10(1): 67–101.

Kalla, Joshua L, and David E Broockman. 2016. "Campaign contributions facilitate access to congressional officials: A randomized field experiment." *American Journal of Political Science*, 60(3): 545–558.

Kang, Karam. 2016. "Policy influence and private returns from lobbying in the energy sector." *The Review of Economic Studies*, 83(1): 269–305.

Kang, Karam, and Robert A Miller. 2022. "Winning by Default: Why is There So Little Competition in Government Procurement?" *The Review of Economic Studies*, 89(3): 1495–1556.

Kim, In Song, Jan Stuckatz, and Lukas Wolters. 2020. "Strategic and Sequential Links between Campaign: Donations and Lobbying."

Kleven, Henrik Jacobsen. 2016. "Bunching." *Annual Review of Economics*, 8(1): 435–464.

Kleven, Henrik J, and Mazhar Waseem. 2013. "Using notches to uncover optimization frictions and structural elasticities: Theory and evidence from Pakistan." *The quarterly journal of economics*, 128(2): 669–723.

Le, Thanh, and Erkan Yalcin. 2018. "Lobbying, campaign contributions, and electoral competition." *European Journal of Political Economy*, 55: 559–572.

Mironov, Maxim, and Ekaterina Zhuravskaya. 2016. "Corruption in procurement and the political cycle in tunneling: Evidence from financial transactions data." *American Economic Journal: Economic Policy*, 8(2): 287–321.

MOE. 2018. *From private funders to public contractors (Spanish).*

MOE. 2019. *Maps and electoral risk factors: elections of local authorities in Colombia 2019 (Spanish).*

Moore, Charity Troyer, Rohini Pande, and Simone Schaner. 2025. "Scaling Accountability: Experimental Evidence on Impacts of Citizen-Led Audits on Social Protection Delivery and Election Outcomes."

OECD. 2019. *Public Procurement in Germany.*

OECD. 2020. *Government at a Glance: Latin America and the Caribbean 2020.*

Olken, Benjamin A. 2007. "Monitoring corruption: evidence from a field experiment in Indonesia." *Journal of political Economy*, 115(2): 200–249.

Powell, Eleanor Neff, and Justin Grimmer. 2016. "Money in exile: Campaign contributions and committee access." *The Journal of Politics*, 78(4): 974–988.

Riaño, Juan Felipe. 2021. "Bureaucratic nepotism." *Available at SSRN 3995589*.

Ruiz, Nelson A. 2021. "The power of money. the consequences of electing a donor funded politician." *SSRN*.

Rust, John. 1987. "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher." *Econometrica*, 55(5): 999–1033.

Saavedra, Santiago. 2024. "Technology and State Capacity: Experimental Evidence from Illegal Mining in Colombia." *Available at SSRN 3933128*.

Schoenherr, David. 2019. "Political connections and allocative distortions." *The Journal of Finance*, 74(2): 543–586.

Szucs, Ferenc. 2023. "Discretion and favoritism in public procurement." *Journal of the European Economic Association*.

Teso, Edoardo. 2023. "Influence-Seeking in U.S. Corporate Elites' Campaign Contribution Behavior." *The Review of Economics and Statistics*, 1–34.

Titl, Vitezslav, and Benny Geys. 2019. "Political donations and the allocation of public procurement contracts." *European Economic Review*, 111: 443–458.

Transparency International Colombia, TIC. 2019. *Elections and public contracts in Colombia: 2018-2019.*

Transparency International Colombia, TIC. 2024. *Second report on elections and public contracts in Colombia.*

Tullock, Gordon. 1972. "The Purchase of Politicians." *Western Economic Journal*, 10(3): 354–355.

van Dijk, Bureau. 2024. "ORBIS."

Weaver, Jeffrey. 2021. "Jobs for Sale: Corruption and Misallocation in Hiring." *American Economic Review*, 111(10): 3093–3122.

World Bank. 2020. "Enhancing Government Effectiveness and Transparency: The Fight Against Corruption."

Zamboni, Yves, and Stephan Litschig. 2018. "Audit risk and rent extraction: Evidence from a randomized evaluation in Brazil." *Journal of Development Economics*, 134: 133–149.

Online Appendix

A Political Donations and Public Contract Allocation

A.1 Public procurement categories

Public procurement in Colombia is governed by Law 80 of 1993, establishing the General Contracting Statute of the Public Administration. The law defines the public procurement categories and the requisites for public agencies to use each type of procedure. Law 1150 of 2007 further introduced efficiency and transparency measures to Law 80 of 1993, most of which consisted of stronger requisites for participating in competitive procedures. Below we describe each procurement.

Direct (discretionary): contracts with a maximum of one year to support bureaucratic/administrative tasks. The public agency can define the technical requirements and assign the contractor with complete discretion as long as the selected contractor meets the requirements defined for the contract execution. The contractor finishing a contract can receive another through direct procurement immediately after, and there are no value limits.

Minimum value and short selection (discretionary): open bid contracts whose value is lower than 10% of the yearly budget of the public agency and are assigned in less than a day to the offer with the minimum value. Public offices issuing minimum value contracts do not require the establishment of a necessary level of experience or technical skills.

Merits contest: assigned based on open-bid competition. A technical proposal is evaluated, and the best-suited for the specific requirement is chosen. Contest assigned contracts are usually used for consultancy or technical assistance in public program execution.

Open tender: open-bid competition for contracts with large values and long-term execution. Usually used for infrastructure projects. Proposals are scored based on different technical aspects, with price being the main factor defining the assignment.

Special procurement regime: some public agencies are not subject to the regulations established by Law 80 of 1993, so they do not need to follow the categories described above but instead have their own procedures, adjusted as required depending on their needs. Public universities and hospitals are part of the special procurement regime.

A.2 Additional details

Figure A1: Journalist covering corruption cases involving political campaign donors



Figure A2: Link donors and contractors with National ID

Contractors data

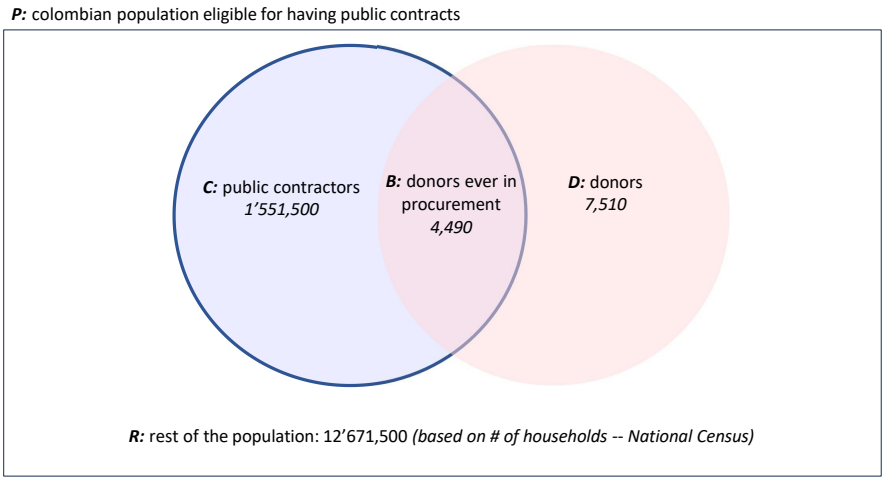
typeproviderid	providername	nationalID
cedula de ciudadania	leonardo urie…	177477
nit	jorge humbert…	178880
nit	jorge humbert…	178880
nit	corporacion r…	218591
cedula de ciudadania	elias alberto…	281020

Donors data

nationalID	donor_name	legal_person
177477	leonardo alayon	Person
178880	antonio lopez	Person
188241	lito cauca	Firms
188241	lito cauca	Firms
196940	felipe benavide…	Person

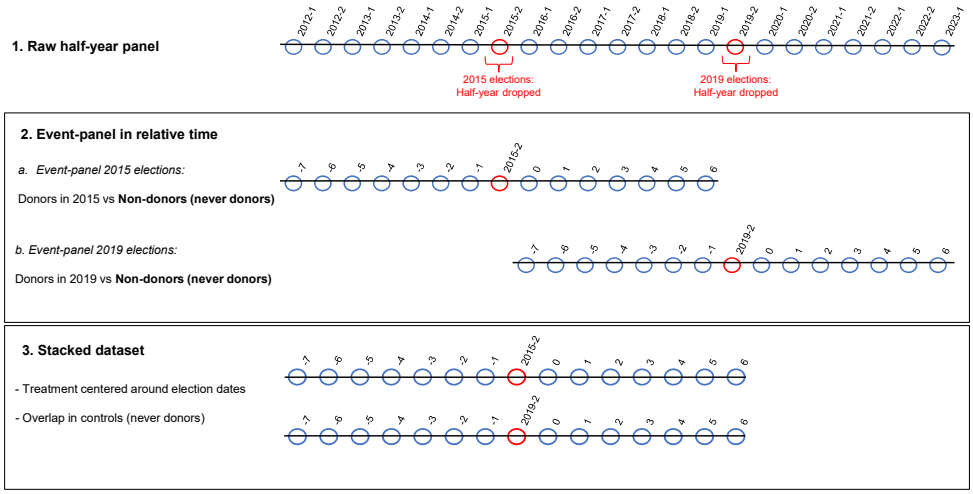
Note: The figure exemplifies how the data is merged between donors and contractors dataset. Note that the national ID coincides for the same individuals in both datasets. In the contractors dataset, the column *typeproviderid* takes the value of "cedula de ciudadania" and "nit", which are the names of the ID for individuals and firms respectively. Thus we are able to identify if the contract was awarded to a firm or an individual. In the donors data, the column *legal_person* identifies whether the donor was a person or a firm. The first match between the two datasets correspond to a Person-person match, so the same individual donating is receiving the contract. The second match in the donors sample is merged with two observations. The ID in the donors data is identified as person, while the column *typeproviderid* in the contractors identifies the two observations as firms. The merged firms in this case are identified as donors a long as the national ID coincide with a person donating, which usually corresponds to the CEO or manager. In cases where the national ID in the donors is identified as firm in both datasets, firms are also defined as donors.

Figure A3: Sample description - 2012 to 2023



Note: The figure illustrates the sample that is being used for the estimations. Our data consist of the population of contractors (blue circle) and population of donors (red circle), both of which are a subset of the Colombian population. From the red circle, we only observe outcomes for those that have ever being in the procurement system (intersection between blue and red). Thus, outcomes for donors not receiving contracts are coded as zero. We simulate the population of non-donors never registered in the procurement system (rest of the population) based on the number of households reported by the 2018 National Census. We assume that each household represents at least one individual who would be eligible for donating and obtaining a public contract.

Figure A4: Stacking procedure description



Note: The figure describes the stacking procedure. The first panel illustrates the structure of the raw data. Blue half-years will be included in the stacking. Red half-years include the month of elections (October) and are dropped from the sample as: i) there is a ban in procurement between July and October, which might affect the contract distribution, and ii) during November and December of the election year, just before the winning candidate take position into office, it is not possible to disentangle whether contracts awarded come directly from the outgoing mayor or indirectly through the incoming mayor. The second panel describes for each event (election) the normalized periods before and after the electoral half-year. Note that post-periods for the 2015 elections dataset overlap with the pre-periods of the 2019 elections dataset. For each event, donors are compared with never donors. The third panel show how both event-datasets are stacked one on top of the other. As shown in the second panel, the stacking imply that there is overlap in the control units. Equation 1 include fixed effects interacted with indicators for each event-dataset to account for overlap.

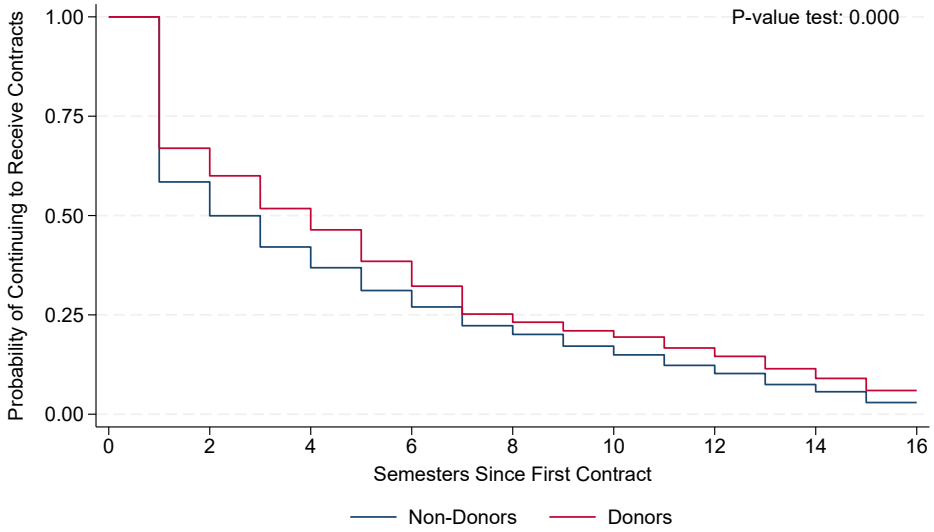
Table A1: Summary Statistics of Donors

Panel A: All donors	Mean	Max.	Std. Dev.	Obs.
Supported candidates (#)	1.008	4	0.103	21,065
Donated in three elections (%)	0.011	1	0.104	21,065
Had contract before elections (%)	0.169	1	0.375	21,065
Had contract after elections (%)	0.162	1	0.369	21,065
Donated value (million COP)	7.994	500	16.401	21,065
Panel B: Donors with contracts	Mean	Max.	Std. Dev.	Obs.
Contracts after elections (#)	4.641	208	8.346	3,421
Contracts supported municipality (%)	0.490	1	0.491	3,421
Contracts supported region (%)	0.880	1	0.321	3,421
Donated value (million COP)	6.321	253	11.594	3,421

Notes: This table shows the summary statistics for the sample of donors who donated in each election (2015, 2019, 2023). Each observation is a donor. Panel A shows summary statistics for all donors. Panel B includes only donors who had contracts in the legislative period.

A.3 Additional results

Figure A5: Survival curve by donation status



Note: The figure plots the Kaplan-Meier survival graph. The y-axis indicates the probability of survival over time for donors (red) and non-donors (blue), over half-years after the first contract is received by a firm or individual ever (or never) donating. The p-value reported on top of the figure test for the null that the two curves are not different. Significant p-value indicates that we fail to reject equal distribution of probability of survival. The graph then indicates that donors have a larger probability of staying in the procurement system than non-donors.

Table A2: Effect of Donating to a Political Campaign

Dep. Variable	Pr(contract)	Log(contract value)
	(1)	(2)
Donor×Post	0.028***	0.17***
	(0.0015)	(0.0097)
Number of observations	398,412,056	398,412,056
Number of donors	12,574	12,574
Number of non-donors	14,222,715	14,222,715
Non-donor Mean Dep. Var. before	0.099	0.655
Individual × Election FE	Yes	Yes
Time × Municipality × Election FE	Yes	Yes
Controls × Time dummies	Yes	Yes

Notes: The unit of observation is at the individual-half-year level. *Donor* equals one for individuals/firms donating to a political campaign. *Post* equals 1 for periods after the elections. Contract value is log-transformed. The intensive margin is defined following Chen and Roth (2022) and set to $-x = -1$ for non-recipients. The mean of the dependent variable is measured for non-donors in the pre-period, conditional on ever receiving a contract. Pr(contract) equals one if individual reported at least one contract per period. Controls include the cohort of entry (coded as 0 if no entry yet by the time of donation), periods of experience before the election, and type of unit (individual or firm). Standard errors clustered at the individual level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

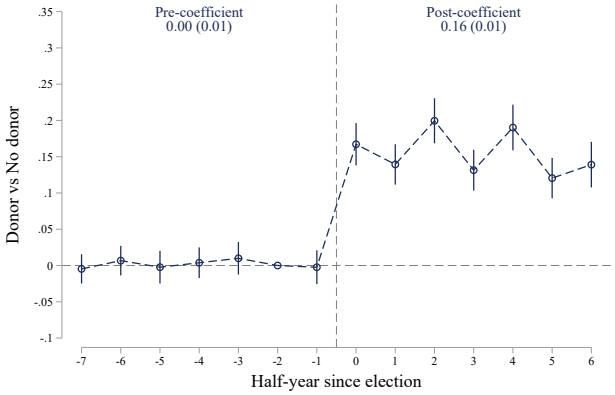
Table A3: Effect of Donating to a Political Campaign - Non-donors Population Robustness

Dep. Variable	Pr(contract)	Log(contract value)
	(1)	(2)
Donor×Post	0.025***	0.15***
	(0.0015)	(0.0097)
Number of observations	308,907,172	308,907,172
Number of donors	12,574	12,574
Number of non-donors	11,026,112	11,026,112
Non-donor Mean Dep. Var. before	0.099	0.655
Individual × Election FE	Yes	Yes
Time × Municipality × Election FE	Yes	Yes
Controls × Time dummies	Yes	Yes

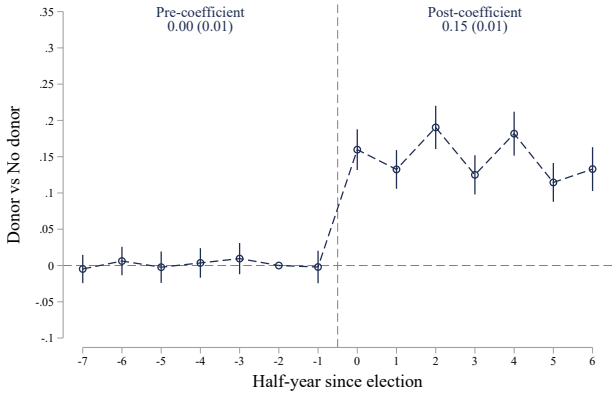
Notes: The unit of observation is at the individual-half-year level. The non-donors group exclude the number of individuals (households) per municipality defined as poor based on the Multidimensional Poverty Index from the 2018 National Census. *Donor* equals one for individuals/firms donating to a political campaign. *Post* equals 1 for periods after the elections. Contract value is log-transformed. The intensive margin is defined following Chen and Roth (2022) and set to $-x = -1$ for non-recipients. The mean of the dependent variable is measured for non-donors in the pre-period, conditional on ever receiving a contract. Pr(contract) equals one if individual reported at least one contract per period. Controls include the cohort of entry (coded as 0 if no entry yet by the time of donation), periods of experience before the election, and type of unit (individual or firm). Standard errors clustered at the individual level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A6: Effect of Donating to Political Campaign - Log Transformation Robustness

(a) Log(contract value) - x = 0.5



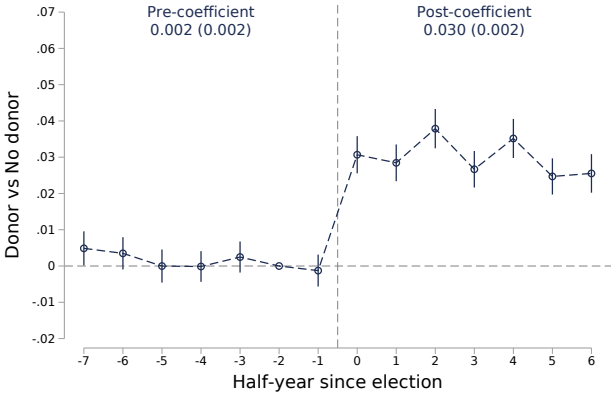
(b) Log(contract value) - x = 0.25



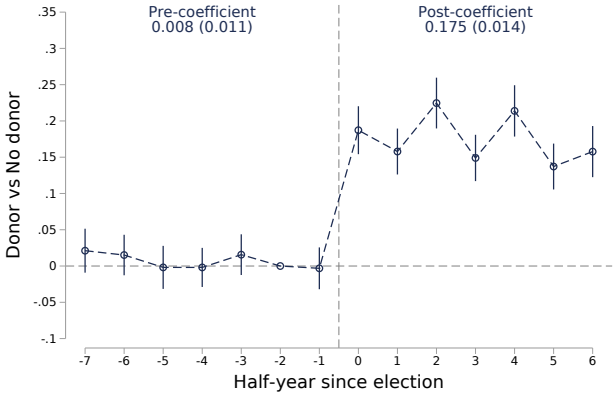
Note: The figure reports the point estimate and the 95% confidence intervals from estimating an event study version of equation 1 for the overall population. It also reports the pooled coefficients for the periods before and after. Standard errors clustered at the individual level. The contract value is log-transformed. The intensive margin of the log transformation is defined following Chen and Roth (2022) and set to $x = -0.5$ and $x = -0.25$ for non-recipients. Pr(contract) equals one if the contractor reports having at least one contract per period.

Figure A7: Effect of Donating to Political Campaign - No Cohort Fixed Effects

(a) Pr(contract)

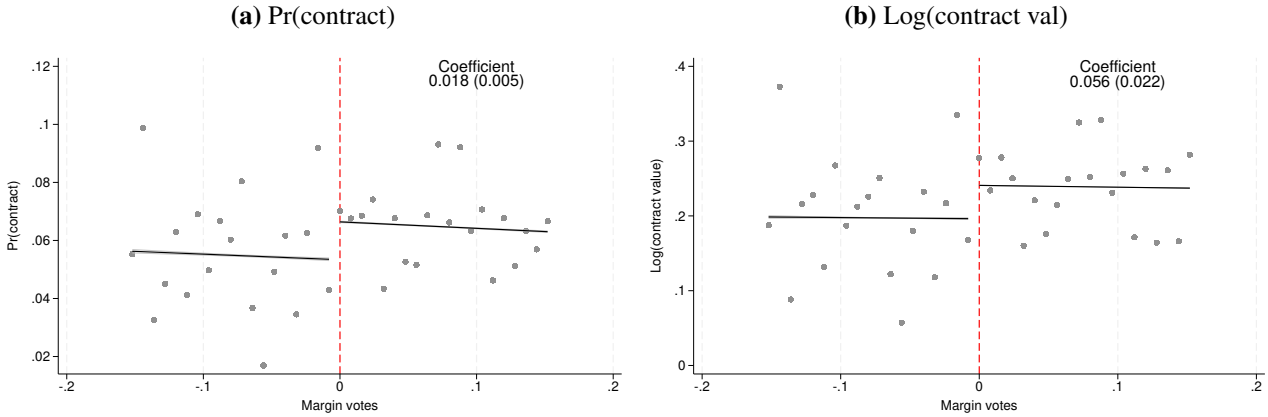


(b) Log(contract value)



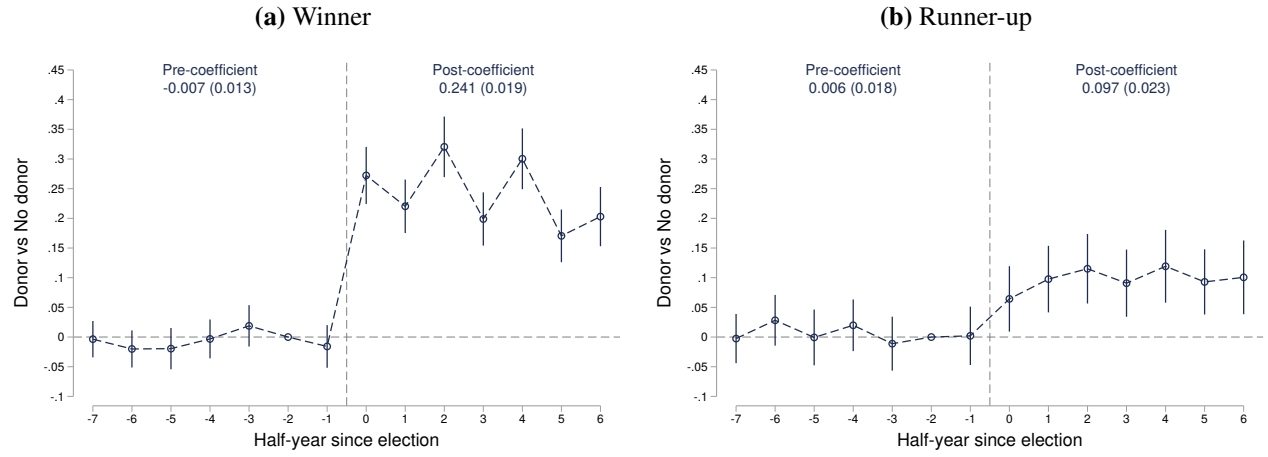
Note: The figure reports the point estimate and the 95% confidence intervals from estimating an event study version of equation 1 for the overall population. It also reports the pooled coefficients for the periods before and after. Standard errors clustered at the individual level. The contract value is log-transformed. The intensive margin of the log transformation is defined following Chen and Roth (2022) and set to $x = -1$ for non-recipients. Pr(contract) equals one if the contractor reports having at least one contract per period.

Figure A8: Effect of Donating the Winner in Close Elections



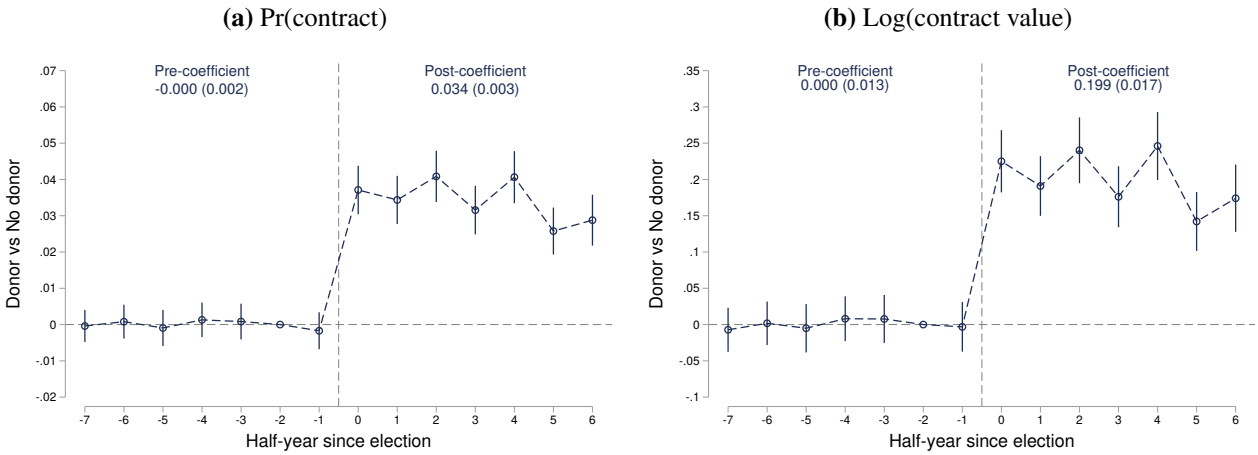
Note: The figure reports the discontinuity plot around the vote margin between the winner and runner-up candidates for the 2015 and 2019 elections. The dots represent the binned outcomes, the dark line correspond the the linear fit. Dashed red line indicates the 0 vote margin. The figure displays the bins around the optimal bandwidth defined as in Calonico, Cattaneo and Farrell (2020). The coefficient reported on top is estimated using a regression discontinuity design with the following equation: $Y_i = \alpha + \beta \cdot \mathbb{1}[\text{Winner vote margin}_i > 0] + \gamma \cdot \text{Winner vote margin}_i + \theta \cdot \mathbb{1}[\text{Winner vote margin}_i > 0] \times \text{Winner vote margin}_i + \varepsilon_i$, Where $textWinnervotemargin_i > 0$ for donors to the winner. Standard errors clustered at the individual level. The contract value is log-transformed. The intensive margin of the log transformation is defined following Chen and Roth (2022) and set to $x = -1$ for non-recipients. Pr(contract) equals one if the contractor reports having at least one contract per period.

Figure A9: Effect of Donating to a Political Campaign by Supported Candidate - log(Contract Value)



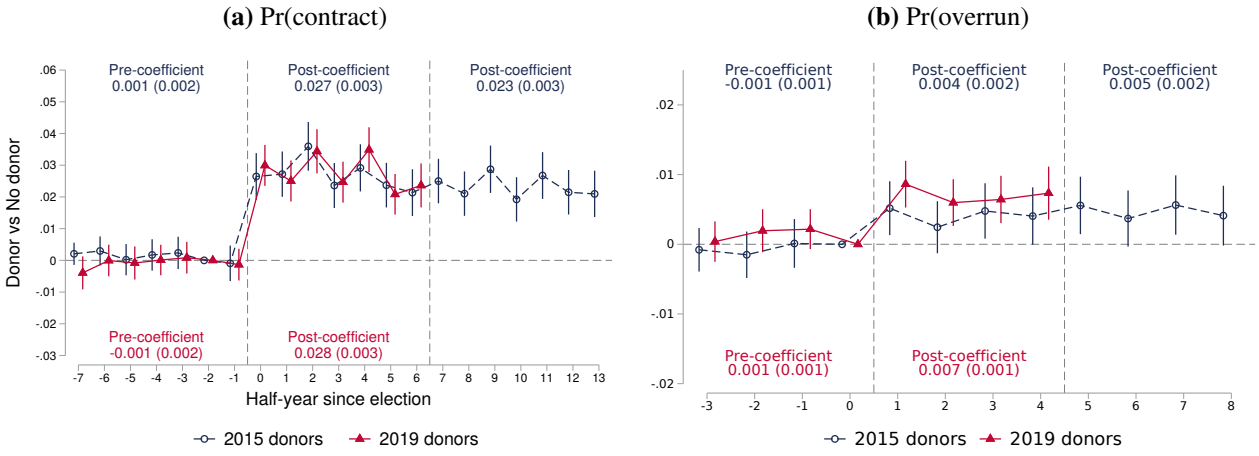
Note: The figure reports the point estimate and the 95% confidence intervals from estimating an event study based on equation 1 independently for each election sub-panel, and extending for each the respective post periods, and separating the donors' group by the position of the supported candidate in the elections, while leaving the non-donors group constant. It also reports the pooled pre and post coefficients. Standard errors clustered at the individual level. The contract value is log transformed. The intensive margin of the log transformation is defined following Chen and Roth (2022) and set to $x = -1$ for non-recipients.

Figure A10: Effect of Donating to a Political Campaign in Municipalities with Close Elections



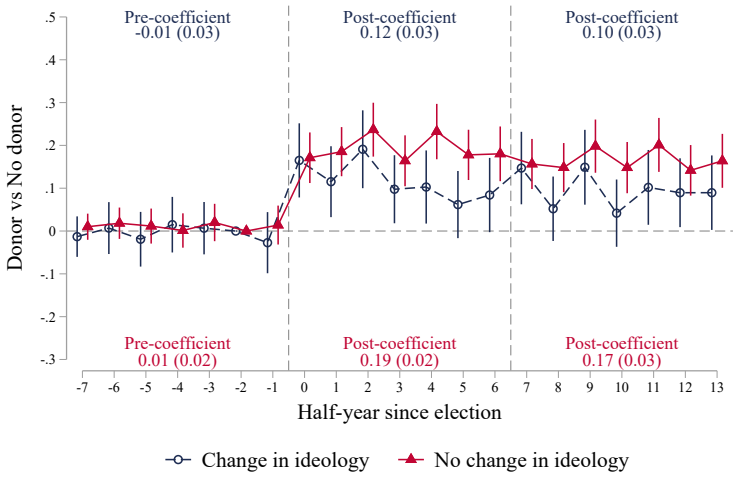
Note: The figure reports the point estimate and the 95% confidence intervals from estimating an event study version of equation 1 for the overall population in municipalities with close elections, defined as municipalities where the difference in votes between the winner and runner-up candidates is close to zero. It also reports the pooled coefficients for the periods before and after. Standard errors clustered at the individual level. The contract value is log-transformed. The intensive margin of the log transformation is defined following Chen and Roth (2022) and set to $x = -1$ for non-recipients. Pr(contract) equals one if the contractor reports having at least one contract per period.

Figure A11: Long-term Effect of Donating to a Political Campaign



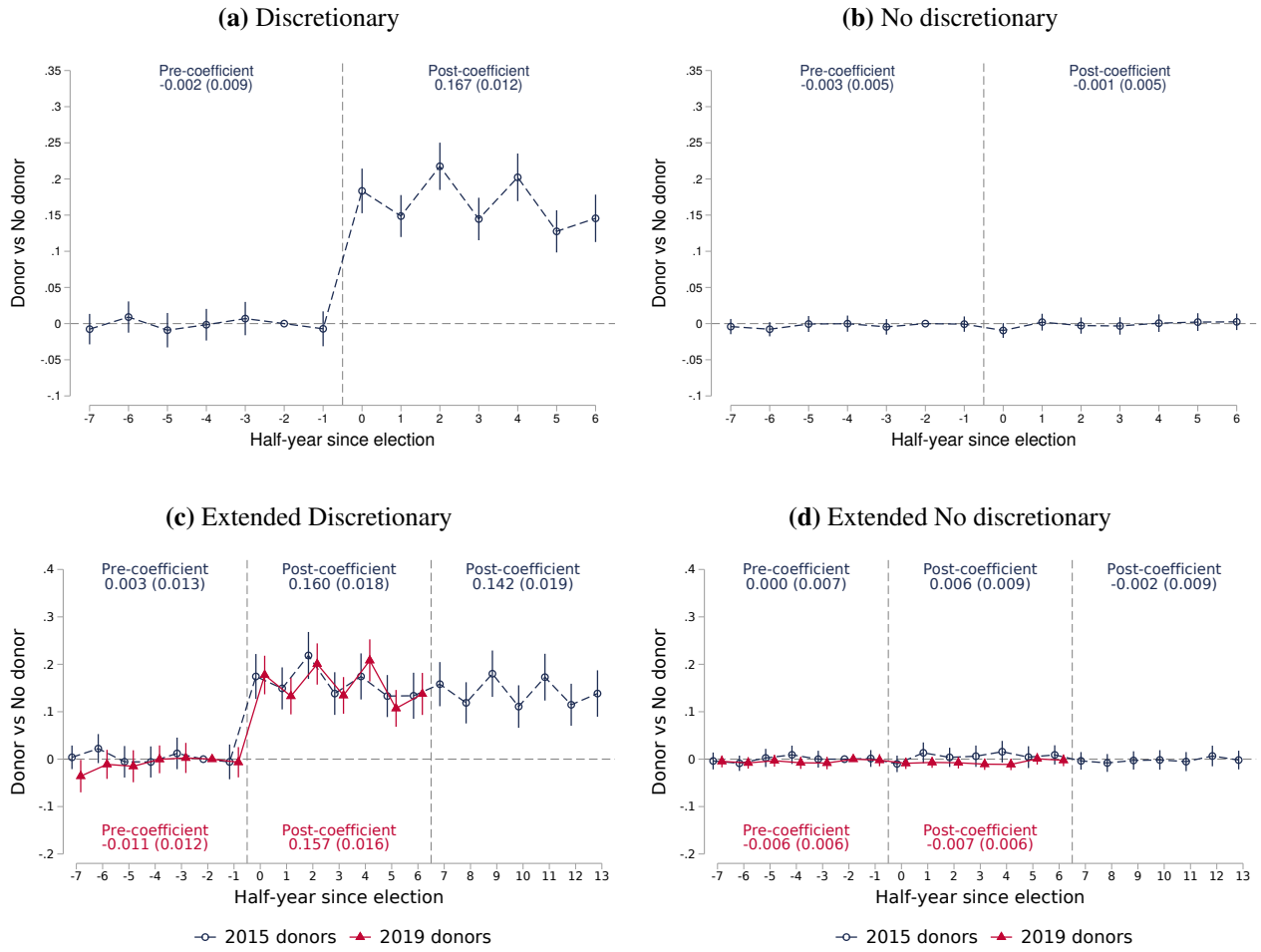
Note: The figure reports the point estimate and the 95% confidence intervals from estimating an event study based on equation 1 independently for each election sub-panel, and extending for each the respective post periods. Blue coefficients are for the 2015 elections. The red coefficients are for the 2019 elections. It also reports the pooled pre and post coefficients. Standard errors clustered at the individual level. Panel (a) for the Pr(contract) aggregates the data at the individual-by-half-year level. Panel (b) for the Pr(overrun) aggregates the data at the individual-by-year level.

Figure A12: Effect of Donating to a Political Campaign by Ideology Turnover - Log(contract value)



Note: The figure reports the point estimate and the 95% confidence intervals from estimating an event study based on equation 1 comparing 2015 donors against non-donors, and separating between those receiving contracts in municipalities that in 2019 elections changed / not changed ideology of the political party in power. Blue coefficients are for the changing municipalities. The red coefficients are for not changing municipalities. It also reports the pooled pre and post coefficients. The contract value is log-transformed. The intensive margin of the log transformation is defined following Chen and Roth (2022) and set to $x = -1$ for non-recipients.

Figure A13: Effect of Donating to Political Campaign by Procurement Type - log(Contract Value)



Note: The figure reports the point estimate and the 95% confidence intervals from estimating an event study based on equation 1 separating by type of procurement. Panel (a) and (b) report the results from estimating the stacked difference-in-differences for the two mayoral elections (2015 and 2019). Panel (c) and (d) estimate each election independently, extending the panel for those that donated in 2015 to all possible post-periods. The figures report the pooled pre and post coefficients. Standard errors clustered at the individual level. The average contract value is log transformed. The intensive margin of the log transformation is defined following Chen and Roth (2022) and set to $x = -1$. *Discretionary:* include Direct and Minimum Value. *Non-discretionary:* include Contest, Tender and Selection.

B Curbing the Influence of Political Donations

B.1 Partner organizations

Open contracting partnership – NGO: It is an independent non-profit organization that supports government, businesses, and civil society to implement reforms and innovations aimed at better and more transparent public procurement. The organization works in over fifty countries, including Colombia. Open Contracting Partnership supports the project by allowing us to send communications (e-mail and physical) under their name.

Anti-corruption Institute (Instituto Anticorrupción) – NGO: it is a Colombian non-profit organization founded in 2018 with the intention of developing research and analysis on the causes and effects of corruption, as well as potential solutions to it. As partners, the Anti-corruption Institute supports the project by allowing us to send communications (e-mail and physical) under their name.

Inspector's General Office (Procuraduría General de la Nación) – Government agency: it is the national level government office overseeing public sector workers and presenting the required legal actions whenever a public servant is found in unlawful behavior. Part of the office's responsibility is to investigate inefficient procurement as long as the municipal mayor, contractor, and other relevant actors may be involved in corruption or other types of misbehavior. The Inspector General Office is related to the project only by being knowledgeable about the letters that will mention them as receptors of the data. We consider such coordination might increase the policy implications of the intervention, as it might increase the efficiency by which the office identifies probable unlawful behavior.

B.2 Letter draft

Figure B1 shows a draft of the letter received by mayors. Highlighted in yellow, there is a paragraph that mentions that attached to the letter, there is the list of donors of the latest mayoral campaigns in the municipality. For the treatment arms that do not receive an attachment with the letter, there paragraph is not included. Highlighted in red there are the parts of the letter that mention an specific authority to share the donors procurement data with. It can mention the Inspector General Office (government), or multiple investigative media outlets (journalist). In cases were no authority is mentioned, the letter does not include the red highlighted text. The rest of the text remains regardless of the treatment arm.

Figure B2 shows an example of the donor list received by mayors . The first and second column mention the national ID and name of the donor, respectively. The third column mentions the name of the candidate that was supported by the donor, while the fourth mention the total donated amount. The rest of the column report whether the donor has already received contracts with the new mayoral administration, and the value of such contracts if they have received. Similarly, it also reports if the donor received contracts under the previous mayor, and the total amount of the contracts received.

B.3 Balance

We test for balance across randomized municipalities on (i) municipal level variables, including procurement history, electoral results, donors' behavior and municipal characteristics, and (ii) observable donor characteristics, including their total donated value, contracts awarded in the previous mayoral period, the existence of a registry in the procurement system, and the ranking of the donor relative to other donors of the same candidate based on the donated value. We also test for balance across omitted and included donors. While only 164 municipalities received a list of donors with an omitted individual, we randomized for all treatment arms to ensure global balance.

Figure B1: Draft letter for elected mayors

Bogotá, D.C., May 1st, 2024

Dear Doctor,

<<NAME>> <<LAST NAME>>
Mayor of the municipality of **<<MUNICIPALITY NAME>>**

Subject: Political donations and public procurement in your municipality
Copied to: ***<<Contact government organizations or other civil society organizations>>***

As part of an independent research study, **Open Contracting Partnership (OCP)** in partnership with the **Anti-Corruption Institute (IA)** wants to remind you of the existing and specific legal restrictions on the allocation of public contracts to political campaign donors in your municipality.

As you may be aware, Colombia has adopted strict measures to promote transparency in public procurement, particularly regarding political campaign donors.

- **The Law 1474 of 2011**, in its second article, establishes that natural or legal persons who have made contributions to the political campaign of the mayor-elect ***may not receive contracts*** when such donations exceed the limits established by this law. In addition, it extends this restriction to family members of natural persons and to the legal representatives, partners, and members of the board of directors of legal entities.
- **The Statutory Law 1475 of 2011,** in its twenty-seventh article, ***prohibits political donations*** from individuals whose main income in the previous year comes from contracts with the public sector.
- Likewise, **Law 80 of 1993,** in its eighth article, establishes a detailed list of ***inabilities and incompatibilities*** for contracting with the state.

Attached to this letter you will find the list of donors to the political campaigns in your municipality during the last elections of 2023, as well as the values donated by each of them. We have included information on public procurement and donation amounts based on information available on the *Clear Accounts in Elections* page and on the *Open Data portal* as **of April 30, 2024**.

We hope that this legal framework and detailed cross-checking of information will be valuable for you to manage the public resources of your municipality and, above all, useful for complying with all the restrictions provided for by law. We remind you that as part of our process of empowering local actors and with the aim of surveillance and monitoring the contracting process, all the information contained in this letter, as well as the attached documents and databases, are being shared with ***<<Contact government organizations or other civil society organizations>>***

If you have any doubts regarding this communication or its content, we invite you to consult the portal for resolved questions: https://www.open-contracting.org/studies/donnors_study

Kind regards

The Open Contracting Partnership Colombia Team
The Anti-Corruption Institute Team.

This communication is addressed solely and exclusively to the public office or person to whom reference is made. All the information mentioned and attached to this communication comes from official public sources of the Colombian Government. Open Contracting Partnership, OCP, is committed to the legal, lawful, confidential, and secure treatment of your data, so any additional information outside of what is available in the public domain will be treated in accordance with Colombian regulations on data management.

Figure B2: Attached donor list

ID del donante (Cedula o NIT)	Nombre completo del donante	Dono al candidato...	Valor donado	Recibio contratos durante la actual administracion con corte al 30/04/2024	Valor total contratado durante la actual administracion con corte al 30/04/2024	Recibio contratos durante la administracion pasada	Valor total contratado durante la administracion pasada
30341103	Myriam Yolanda Rojas Mafla	Campo Elias Ramirez Padilla	$30.000.000	No	-	No	-
91179414	Robinson Rodriguez Sarmiento	William Mantilla Serrano	$51.000.000	No	-	Si	$120.205.904
1098610878	Yuly Andrea Mantilla Mantilla	William Mantilla Serrano	$37.000.000	No	-	Si	$125.232.376
9007546468	Partido Politico Centro Democratico	William Mantilla Serrano	$10.000.000	No	-	No	-
13512558	Sabal Mantilla Rivero	Dalida Prada Villamizar	$4.500.000	No	-	No	-
70119713	Mario De Jesus Osorio Zora	Blanca Azucena Rodriguez Romero	$5.813.745	No	-	No	-
1095806423	Laura Tatiana Florez Prada	Blanca Azucena Rodriguez Romero	$290.000	No	-	No	-
1095920214	Jose Luis Prada Rueda	Mauricio Gomez Nino	$40.000.000	No	-	No	-
13826970	Oscar Clavijo Camargo	Mauricio Gomez Nino	$7.500.000	No	-	No	-
37727297	Jackeline Gomez Carreno	Mauricio Gomez Nino	$6.000.000	No	-	Si	$96.072.696
1095920583	Cristian Mauricio Gomez Perez	Mauricio Gomez Nino	$6.000.000	No	-	No	-

Table B1: Treatment compliance

Dep. Variable	Delivered		Opened	
	(1)	(2)	(3)	(4)
A. Inspector General	1.000***		0.995***	
	(0.000)		(0.005)	
Inspector General + no list		1.000***		0.991***
		(0.000)		(0.009)
Inspector General + list		1.000***		1.000***
		(0.000)		(0.002)
B. Investigative Journalist	1.000***		0.991***	
	(0.000)		(0.007)	
Investigative Journalist + no list		1.000***		0.991***
		(0.000)		(0.009)
Investigative Journalist + list		1.000***		0.991***
		(0.000)		(0.009)
C. No CC	1.000***		0.991***	
	(0.000)		(0.007)	
No CC + no list		1.000***		0.991***
		(0.000)		(0.009)
No CC + list		1.000***		0.991***
		(0.000)		(0.009)
Mean of controls	0.000	0.000	0.000	0.000
Number of municipalities	876	876	876	876
Block FE	Yes	Yes	Yes	Yes

Notes: The unit of analysis is the municipality, a regression of each treatment arm on wether the municipality received the treatment letter and wether the email was recorded as opened by the mayor. *Inspector General* is for the treatment letter carbon copying the relevant public office that oversight public procurement. *Investigative Journalist* is for the treatment letter carbon copying investigative journalist. *No CC* is for municipalities receiving the treatment letter without carbon copy additional organizations. *No list* is for treatment letters not including the donor list as attachment. *List* group the treatment letter including the full and partial list of donors as attachment. The mean of the outcomes equals 0 for control municipalities (not receiving a letter). *Block FE* is for randomization block fixed effects. Standard errors clustered at the municipal level are in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We test for balance in municipal characteristics across treatment arms in Table B3 by estimating a linear regression comparing municipal outcomes for each treatment arm against the constant. We include randomization block fixed effects and robust standard errors. The bottom of the table reports the p-value of a joint significance test for the null that all the differences across treatment arms are jointly equal to zero.

We test for balance in donor level variables across treatment arms in Table B2 by estimating a linear regression comparing outcomes for each treatment arm against the constant. We include randomization block fixed effects and standard errors clustered at the municipal level (randomization level). Finally, we test for balance between omitted and included donors in Table B4 by estimating a linear regression comparing outcomes for each treatment arm against the constant. We include donor randomization block fixed effects and standard errors clustered at the municipal level.

Table B2: Balance on donor characteristics by municipal treatment arms

Dep. Variable	Donated val. last election (1)	# contracts 2020-2023 (2)	Contracted val. 2020-2023 (3)	Had contract before 2024 (4)	Had contract since 2024 (5)	Rank donor =1 if highest (6)	Donated above threshold (7)
Control	6.681	0.429	-74.448	0.163	0.041	3.094	0.535
	(1.927)	(0.157)	(92.977)	(0.062)	(0.024)	(0.598)	(0.103)
Placebo letter	7.839	0.429	632.409	0.140	0.039	2.462	0.515
	(2.957)	(0.194)	(533.182)	(0.060)	(0.024)	(0.539)	(0.102)
Letter + no CC + no list	5.003	0.409	-56.538	0.191	0.033	2.049	0.509
	(1.809)	(0.160)	(81.553)	(0.061)	(0.023)	(0.647)	(0.101)
Letter + no CC + full list	5.401	0.394	5.690	0.155	0.035	2.279	0.532
	(1.765)	(0.184)	(48.710)	(0.063)	(0.024)	(0.535)	(0.106)
Letter + no CC + partial list	8.336	0.558	-56.161	0.204	0.034	1.984	0.582
	(3.322)	(0.209)	(97.796)	(0.068)	(0.024)	(0.662)	(0.102)
Letter + CC journalist + no list	6.159	0.574	-18.145	0.188	0.049	3.160	0.486
	(1.732)	(0.176)	(54.410)	(0.061)	(0.024)	(0.643)	(0.101)
Letter + CC journalist + full list	6.624	0.216	25.839	0.186	0.042	3.270	0.571
	(1.891)	(0.167)	(73.390)	(0.061)	(0.024)	(0.649)	(0.107)
Letter + CC journalist + partial list	7.404	0.456	-20.625	0.149	0.029	2.645	0.508
	(1.765)	(0.168)	(69.464)	(0.060)	(0.023)	(0.740)	(0.102)
Letter + CC government + no list	5.350	0.426	-52.795	0.171	0.039	2.955	0.506
	(1.766)	(0.171)	(77.219)	(0.063)	(0.023)	(0.662)	(0.102)
Letter + CC government + full list	5.935	0.706	-70.872	0.185	0.061	3.337	0.496
	(1.795)	(0.245)	(115.682)	(0.066)	(0.026)	(0.987)	(0.103)
Letter + CC government + partial list	5.271	0.248	-42.474	0.137	0.044	2.106	0.570
	(1.801)	(0.162)	(81.997)	(0.061)	(0.024)	(0.568)	(0.107)
N. of donors	8,560	8,560	8,560	8,560	8,560	8,560	8,560
N. of municipalities	876	876	876	876	876	876	876
Joint significance p-value	0.719	0.284	0.995	0.408	0.534	0.574	0.304

Notes: The unit of analysis is the donor for the electoral period 2024-2027. The table shows the average donor characteristics across municipal treatment arms relative to the constant. All regressions include block-fixed effects and standard errors clustered at the municipal level. The bottom of the table reports the p-value of a joint significance test for the difference of each arm treated arm relative to the control group. *Donated value* in million COP is for the total amount donated by an individual donor to a single candidate. *# contracts* and *Contracted value* for 2020-2023 measures the procurement characteristics of donors in the mayoral period before the donation. *Contracted value* in million COP. *Had contracts before 2024* measures whether the donors were already registered contractors at the time of the mayoral period for which they donated started. *Had contracts since 2024* measures if the donor received a contract between January and May of 2024. *Rank donor* measures the ranking of the donor by candidate and municipality based on the amount donated. *Donated above threshold* measures if the total amount donated by an individual or firm is above the legal limit for being allowed to participate in public procurement procedures.

B.4 Additional results

Table B3: Balance on municipal covariates

Panel A: municipal procurement covariates												
Dep. Variable	# contractors			# contracts			# discretionary			Contract value		
Electoral cycle	2012-2015	2016-2019	2020-2023	2012-2015	2016-2019	2020-2023	2012-2015	2016-2019	2020-2023	2012-2015	2016-2019	2020-2023
Control	2.126	3.432	3.510	0.758	1.754	1.631	0.379	0.541	0.754	34.371	69.746	99.349
	(1.830)	(3.120)	(2.894)	(0.613)	(1.566)	(1.368)	(0.270)	(0.471)	(0.667)	(65.331)	(99.983)	(93.836)
Placebo letter	7.282	8.342	6.123	1.605	1.897	1.602	1.004	0.970	0.973	65.687	127.594	173.566
	(6.514)	(7.588)	(5.621)	(1.420)	(1.727)	(1.617)	(0.866)	(0.928)	(1.061)	(86.189)	(138.959)	(172.924)
Letter + no CC + no list	-1.604	-2.114	-2.338	-0.386	-0.737	-0.984	-0.188	-0.280	-0.548	-19.913	84.367	-66.466
	(1.658)	(2.208)	(1.976)	(0.385)	(0.645)	(0.759)	(0.240)	(0.339)	(0.537)	(65.714)	(144.315)	(51.764)
Letter + no CC + full list	-1.940	-2.939	-3.837	-0.438	-0.635	-1.450	-0.328	-0.526	-1.216	-87.962	-96.199	-90.310
	(1.984)	(2.696)	(2.663)	(0.461)	(0.808)	(1.028)	(0.283)	(0.425)	(0.764)	(57.707)	(63.265)	(67.949)
Letter + no CC + partial list	1.111	3.682	5.303	0.245	1.213	3.173	0.204	1.068	2.904	235.007	56.835	114.378
	(2.378)	(5.084)	(5.723)	(0.566)	(1.667)	(3.259)	(0.355)	(1.114)	(2.818)	(267.630)	(82.520)	(120.273)
Letter + CC journalist + no list	-2.191	-3.239	-2.942	-0.519	-1.134	-1.136	-0.296	-0.496	-0.689	30.742	-84.647	-82.144
	(1.696)	(2.233)	(2.021)	(0.401)	(0.670)	(0.789)	(0.244)	(0.329)	(0.557)	(110.911)	(51.077)	(53.395)
Letter + CC journalist + full list	-2.352	-3.587	-4.044	-0.540	-1.171	-1.587	-0.306	-0.446	-0.955	-84.033	-94.288	-86.011
	(2.107)	(2.946)	(2.846)	(0.492)	(0.893)	(1.108)	(0.297)	(0.449)	(0.774)	(56.495)	(63.967)	(67.915)
Letter + CC journalist + partial list	-1.218	-2.486	-2.752	-0.263	-0.694	-1.026	-0.140	-0.311	-0.773	-59.323	-84.801	-76.443
	(2.017)	(2.808)	(2.585)	(0.453)	(0.763)	(0.953)	(0.288)	(0.415)	(0.701)	(56.343)	(59.689)	(62.038)
Letter + CC government + no list	-1.112	-1.245	-0.445	-0.287	-0.382	-0.207	-0.182	-0.224	-0.162	-46.844	-40.481	-19.466
	(1.594)	(2.096)	(1.986)	(0.370)	(0.619)	(0.745)	(0.226)	(0.305)	(0.548)	(44.997)	(50.574)	(52.745)
Letter + CC government + full list	-1.173	-0.989	-0.776	-0.270	-0.397	-0.168	-0.090	-0.080	-0.139	-72.418	-77.161	-46.766
	(1.868)	(2.449)	(2.281)	(0.439)	(0.704)	(0.900)	(0.291)	(0.393)	(0.658)	(53.032)	(58.117)	(57.800)
Letter + CC government + partial list	-0.968	-1.672	-1.161	-0.211	-0.544	-0.609	-0.108	-0.253	-0.360	-46.743	-3.743	-22.995
	(1.104)	(1.575)	(1.370)	(0.266)	(0.490)	(0.574)	(0.167)	(0.217)	(0.391)	(38.321)	(55.883)	(38.260)
Number of municipalities	876	876	876	876	876	876	876	876	876	876	876	876
Joint significance p-value	0.746	0.746	0.574	0.828	0.755	0.568	0.697	0.719	0.608	0.818	0.603	0.696

Panel B: municipal elections and donations covariates												
Dep. Variable	# votes		% votes		# candidates	# donors per candidate			# total donors	Donated value		
Candidate rank	winner	runner-up	winner	runner-up		winner	runner-up	other cand.		winner	runner-up	other cand.
Control	7.965	2.295	0.467	0.045	1.951	3.647	1.026	0.824	5.495	28.811	15.281	4.182
	(5.564)	(1.458)	(0.097)	(0.019)	(0.281)	(0.788)	(0.392)	(0.716)	(1.442)	(9.619)	(10.406)	(5.200)
Placebo letter	14.403	5.392	0.466	0.040	1.978	3.963	0.872	1.185	5.910	26.672	3.031	21.171
	(11.896)	(4.943)	(0.099)	(0.019)	(0.283)	(0.767)	(0.389)	(0.765)	(1.332)	(9.780)	(5.639)	(18.350)
Letter + no CC + no list	0.712	0.616	0.503	0.035	1.959	2.655	0.266	0.540	3.481	13.367	-5.532	-0.531
	(3.590)	(1.906)	(0.098)	(0.019)	(0.295)	(0.757)	(0.367)	(0.781)	(1.372)	(8.971)	(4.353)	(7.407)
Letter + no CC + full list	-0.867	-0.003	0.460	0.050	2.004	3.928	0.648	-0.060	4.517	20.734	0.150	-10.455
	(3.976)	(1.974)	(0.101)	(0.022)	(0.325)	(0.884)	(0.457)	(0.875)	(1.607)	(10.300)	(6.719)	(9.462)
Letter + no CC + partial list	4.806	3.980	0.450	0.058	1.877	3.219	0.703	0.376	4.263	41.081	-6.233	8.480
	(4.752)	(3.301)	(0.104)	(0.023)	(0.299)	(0.833)	(0.505)	(0.593)	(1.299)	(24.111)	(5.330)	(13.714)
Letter + CC journalist + no list	0.460	0.294	0.453	0.046	2.004	3.446	1.530	0.131	5.117	19.323	8.408	-4.018
	(3.363)	(1.685)	(0.098)	(0.019)	(0.296)	(0.799)	(0.509)	(0.559)	(1.244)	(8.927)	(6.600)	(6.626)
Letter + CC journalist + full list	0.567	0.771	0.424	0.053	2.022	4.165	1.084	-0.042	5.154	22.930	9.672	-1.414
	(4.170)	(2.064)	(0.100)	(0.023)	(0.313)	(1.023)	(0.535)	(0.679)	(1.510)	(10.613)	(7.683)	(6.982)
Letter + CC journalist + partial list	1.785	1.313	0.421	0.025	2.131	3.728	1.466	1.522	6.772	32.931	9.141	10.454
	(3.693)	(1.820)	(0.101)	(0.021)	(0.339)	(0.849)	(0.681)	(1.071)	(1.823)	(10.600)	(9.177)	(11.121)
Letter + CC government + no list	-0.051	0.809	0.461	0.048	1.813	3.501	0.630	0.349	4.563	21.683	-2.858	-2.360
	(3.418)	(1.755)	(0.098)	(0.019)	(0.280)	(0.820)	(0.355)	(0.671)	(1.314)	(9.678)	(4.518)	(7.187)
Letter + CC government + full list	0.947	1.874	0.543	0.064	1.531	3.274	0.721	-0.696	3.390	20.766	-1.266	-6.573
	(3.665)	(2.011)	(0.104)	(0.023)	(0.299)	(0.956)	(0.595)	(0.756)	(1.762)	(9.884)	(7.254)	(8.012)
Letter + CC government + partial list	1.071	0.578	0.470	0.040	2.025	3.259	0.730	0.842	4.773	17.852	-0.772	4.521
	(2.790)	(1.624)	(0.103)	(0.021)	(0.322)	(0.832)	(0.460)	(0.888)	(1.430)	(8.861)	(4.605)	(6.425)
Number of municipalities	876	876	876	876	876	876	876	876	876	876	876	876
Joint significance p-value	0.932	0.644	0.663	0.754	0.605	0.663	0.516	0.809	0.839	0.435	0.359	0.764

Panel C: general municipal characteristics and other variables												
Dep. Variable	Population	Area	Height	Dist. capital	Poverty	Andean	Caribbean	Pacific	Orinoquian	Amazonian	# teachers	# students
Control	30.112	1685.766	549.599	108.131	60.410	0.310	0.355	0.140	-0.023	0.218	2.504	6.158
	(18.408)	(761.879)	(206.726)	(20.096)	(5.300)	(0.128)	(0.132)	(0.091)	(0.019)	(0.103)	(1.367)	(3.196)
Placebo letter	68.859	1599.301	638.729	104.643	62.885	0.323	0.336	0.138	0.013	0.190	6.286	12.853
	(59.396)	(748.374)	(203.900)	(20.208)	(5.146)	(0.125)	(0.131)	(0.091)	(0.024)	(0.106)	(5.191)	(10.169)
Letter + no CC + no list	4.665	1391.553	652.448	105.225	62.625	0.300	0.398	0.173	-0.033	0.162	0.909	2.246
	(16.626)	(745.405)	(202.306)	(19.916)	(5.215)	(0.125)	(0.133)	(0.092)	(0.017)	(0.101)	(1.539)	(3.200)
Letter + no CC + full list	-9.087	1670.762	507.357	104.198	62.787	0.345	0.371	0.091	0.012	0.181	-0.549	-0.039
	(19.851)	(868.139)	(213.740)	(20.318)	(5.668)	(0.134)	(0.136)	(0.094)	(0.034)	(0.110)	(1.771)	(3.690)
Letter + no CC + partial list	33.672	2088.980	522.157	89.837	61.633	0.291	0.353	0.109	0.048	0.199	3.241	5.847
	(32.110)	(816.164)	(214.542)	(21.652)	(5.258)	(0.132)	(0.136)	(0.096)	(0.040)	(0.104)	(2.734)	(4.444)
Letter + CC journalist + no list	-2.709	1394.526	640.694	103.629	62.125	0.318	0.407	0.091	0.012	0.171	0.042	0.984
	(15.947)	(740.017)	(203.291)	(19.686)	(5.162)	(0.129)	(0.131)	(0.089)	(0.023)	(0.102)	(1.410)	(2.991)
Letter + CC journalist + full list	-5.234	1612.344	463.230	108.979	64.157	0.272	0.426	0.128	-0.006	0.181	-0.149	0.642
	(21.096)	(797.320)	(230.117)	(20.951)	(5.595)	(0.132)	(0.138)	(0.105)	(0.030)	(0.104)	(1.866)	(3.813)
Letter + CC journalist + partial list	6.392	1335.708	313.903	105.195	64.309	0.272	0.426	0.128	-0.006	0.181	0.814	2.568
	(18.293)	(740.067)	(213.718)	(20.154)	(5.503)	(0.136)	(0.138)	(0.105)	(0.031)	(0.104)	(1.690)	(3.443)
Letter + CC government + no list	8.767	2732.271	614.603	100.123	60.293	0.345	0.353	0.118	0.003	0.181	1.066	3.056
	(15.983)	(969.994)	(205.579)	(20.020)	(5.180)	(0.127)	(0.130)	(0.090)	(0.023)	(0.106)	(1.435)	(3.058)
Letter + CC government + full list	1.056	1318.762	685.194	106.918	59.934	0.309	0.371	0.091	0.012	0.217	0.600	2.021
	(17.926)	(740.963)	(219.354)	(21.256)	(5.491)	(0.135)	(0.139)	(0.093)	(0.034)	(0.106)	(1.581)	(3.302)
Letter + CC government + partial list	5.834	2095.609	387.015	107.028	64.599	0.319	0.355	0.131	-0.004	0.199	0.850	2.642
	(12.565)	(821.055)	(219.673)	(20.097)	(5.567)	(0.138)	(0.135)	(0.097)	(0.032)	(0.105)	(1.035)	(2.396)
Number of municipalities	876	876	876	876	876	876	876	876	876	876	876	876
Joint significance p-value	0.882	0.215	0.269	0.737	0.899	0.998	0.876	0.912	0.717	0.751	0.876	0.908

Notes: The unit is the municipality. The table shows the average covariate per treatment arms. All regressions include randomization block fixed effects and robust standard errors in parentheses. Reported in the bottom the p-value of a joint significance test for the difference relative to the control group. Panel A show balance in municipal procurement outcomes by electoral cycle. *# contractors* is the number of unique contractors in hundreds. *# contracts* and *# discretionary* are the number of contracts and discretionary contracts in thousands. *Contract value* is the total value in hundred million COP. Panel B report on electoral and donation covariates in the last electoral cycle. *# votes* per winner and runner-up in thousands. *% votes* per winner and runner-up relative to all votes in municipality. *# candidates* is the number of participating candidates. *# donors per candidate* reported per winner, runner-up and other candidates. *# donors* is the sum of all donors in the municipality. *Donated value* per winner, runner-up and other candidates in million COP. Panel C report on general characteristics. *Population* in thousand as reported by the 2005 national census. Municipal *Area* in Km^2. *Height* is distance relative to the sea level. *Distance capital* in linear kilometers. *Poverty* is the share of households that reported unmet basic needs in 2012. *Andean*, *Caribbean*, *Pacific*, *Orinoquian* and *Amazonian* measure the share of municipalities in each region. *# teachers* in hundreds and # students in thousands, for 2012.

Table B4: Balance on donor characteristics by omitted and included donor

Dep. Variable	Donated val. last election (1)	# contracts 2020-2023 (2)	Contracted val. 2020-2023 (3)	Had contract before 2024 (4)	Had contract since 2024 (5)	Rank donor =1 if highest (6)	Donated above threshold (7)
Include donor	14.800	0.330	5.088	0.256	0.026	20.002	0.026
	(3.127)	(0.232)	(4.117)	(0.075)	(0.027)	(1.942)	(0.027)
Omitted donor	14.799	0.452	-6.620	0.272	0.029	19.923	0.021
	(3.144)	(0.256)	(22.588)	(0.077)	(0.028)	(1.942)	(0.029)
N. of donors	8,560	8,560	8,560	8,560	8,560	8,560	8,560
Joint significance p-value	1	.27	.61	.26	.61	.42	.68

Notes: The unit of analysis is the donor for the electoral period 2024-2027. The table shows the average donor characteristics across omitted or included donor treatment arms. All regressions include donor block-fixed effects and robust standard errors. The bottom of the table reports the p-value of a joint significance test for the difference of each arm treated arm relative to the control group. *Donated value* in million COP is for the total amount donated by an individual donor to a single candidate. *# contracts* and *Contracted value* for 2020-2023 measures the procurement characteristics of donors in the mayoral period before the donation. *Contracted value* in million COP. *Had contracts before 2024* measures whether the donors were already registered contractors at the time of the mayoral period for which they donated started. *Had contracts since 2024* measures if the donor received a contract between January and May of 2024. *Rank donor* measures the ranking of the donor by candidate and municipality based on the amount donated. *Donated above threshold* measures if the total amount donated by an individual or firm is above the legal limit for being allowed to participate in public procurement procedures.

Table B5: Placebo letter effect on donors procurement outcomes

Dep. Variable	Pr(contract) (1)	Log(contract value) (2)
Donor		
Placebo×Post	0.005	0.036
	(0.003)	(0.022)
Mean of dependent variable	0.003	0.126
N. of obs.	71,752,694	7,1752,694
Number of municipalities	217	217
Number of donors	2,218	2,218
Individual FE	Yes	Yes
Block $\times$ $\mathbb{1}[Donor]$ $\times$ Time FE	Yes	Yes

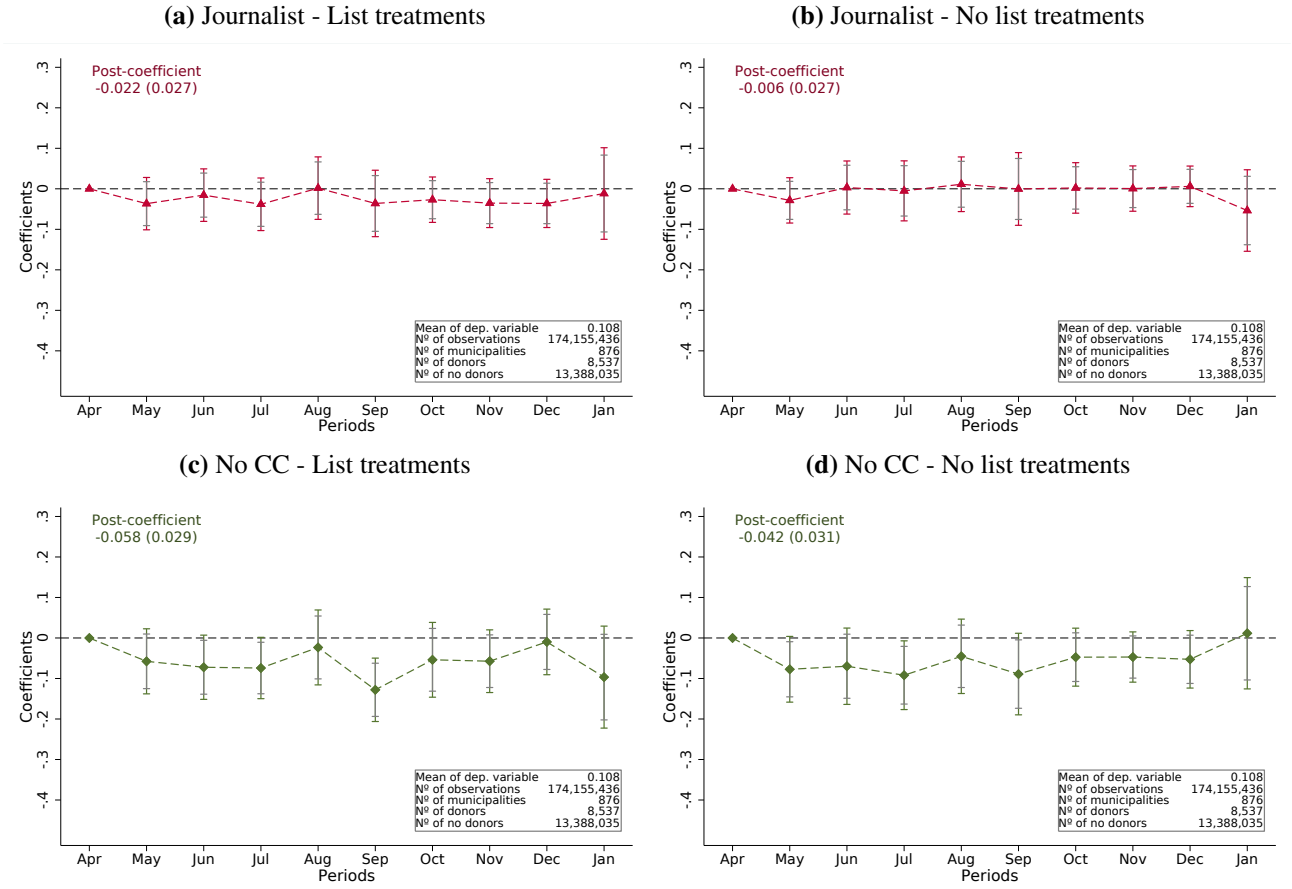
Notes: The unit of analysis is the individual-month, estimating equation 2 on procurement outcomes, comparing only the placebo arm with the pure control. Panel for non-donors estimated but not reported. See Table 2. *Placebo* is for the placebo letter being outside the control group. *Pr(contract)* equals 1 if the donor received a contract in t, 0 otherwise. *log(contract value)* is the value of contracts. The log transformation follows Chen and Roth (2022) and define the intensive margin as $x = -1$ for non-recipients. *Post* equal 1 for periods after the letter were sent to mayors. The mean of the outcomes is measured in the pre-period and is reported in million COP for the contract value. *Donor block FE* is for donor randomization block fixed effects. *Time FE* is month fixed effects. Standard errors clustered at the municipal level are in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B6: Effect of RCT letter on donors procurement outcomes - omitted and included donors

Dep. Variable	Pr(contract) (1)	Log(contract value) (2)
Donor		
A. Inspector General×Post		
Inspector General + no list×Post	0.001	0.004
	(0.002)	(0.015)
Inspector General + list + Omitted donor×Post	-0.014	-0.075
	(0.009)	(0.047)
Inspector General + list + Included donor×Post	-0.006*	-0.040**
	(0.003)	(0.020)
B. Investigative Journalist×Post		
Investigative Journalist + no list×Post	-0.002	-0.014
	(0.003)	(0.018)
Investigative Journalist + list + Omitted donor×Post	0.006	0.037
	(0.006)	(0.033)
Investigative Journalist + list + Included donor×Post	-0.003	-0.019
	(0.002)	(0.016)
C. No CC×Post		
No CC + no list×Post	-0.001	-0.016
	(0.003)	(0.018)
No CC + list + Omitted donor×Post	0.005	0.031
	(0.010)	(0.057)
No CC + list + Included donor×Post	-0.003	-0.021
	(0.003)	(0.018)
Linear combinations P-values		
Inspector General + list: Omitted donor - Included donor	0.387	0.488
Mean dependent variable for donors	0.024	0.425
N. of obs.	174,155,488	174,155,488
Number of municipalities	876	876
Number of donors	8,537	8,537
Individual FE	Yes	Yes
Block $\times$ $\mathbb{1}[Donor]$ $\times$ Time FE	Yes	Yes

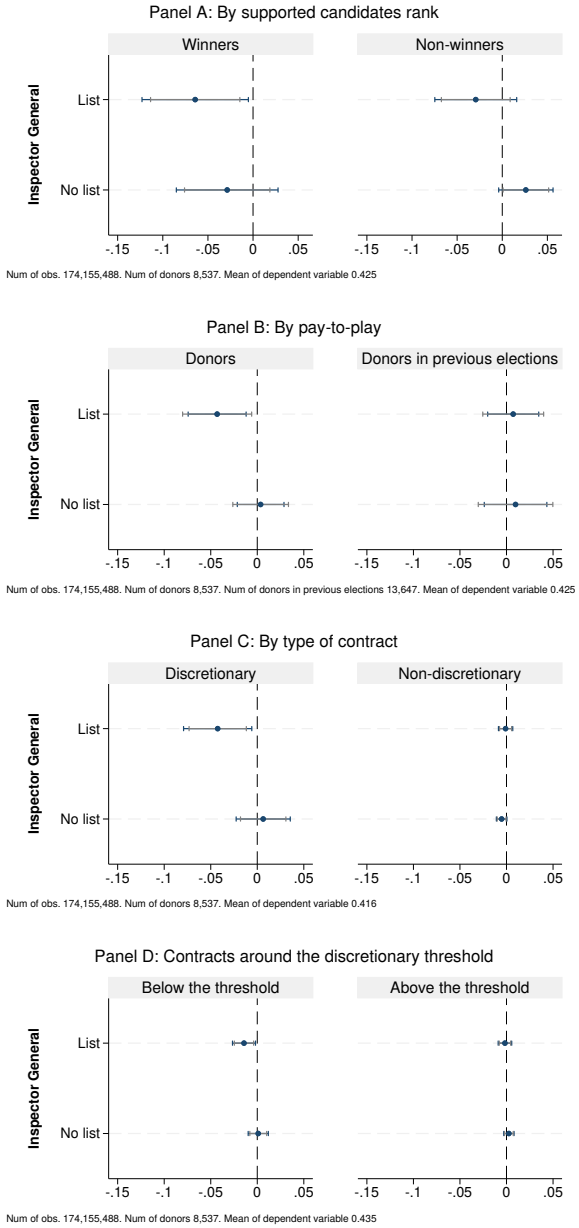
Notes: The unit of analysis is the individual-month, estimating equation 2 on procurement outcomes. Panel for non-donors estimated but not reported. See Table 2. *Inspector General* is for the treatment letter carbon copying the relevant public office that oversight public procurement. *Investigative Journalist* is for the treatment letter carbon copying investigative journalist. *No CC* is for municipalities receiving the treatment letter without carbon copy additional organizations. *No list* is for treatment letters not including the donor list as attachment. *List* group the treatment letter including the full and partial list of donors as attachment. *Pr(contract)* equals 1 if the donor received a contract in t, 0 otherwise. *log(contract value)* is the value of contracts. The log transformation follows Chen and Roth (2022) and define the intensive margin as $x = -1$ for non-recipients. *Post* equal 1 for periods after the letter were sent to mayors. The mean of the outcomes is measured in the pre-period and is reported in million COP for the contract value. *Individual FE* is for individual fixed effects. *Block* $\times$ $\mathbb{1}[Donor]$ $\times$ *Time FE* is for randomization block by donation status by month fixed effects. Standard errors clustered at the municipal level are in parentheses. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure B3: Effect of RCT letter on donors procurement - log(contract value) post-treatment coefficients



Note: The unit of analysis is the individual-month. The figure shows point estimates and 95% confidence intervals from estimating equation 2 on procurement outcomes. Fixed effects for randomization block $\times$ $\mathbb{1}[Donor]$ $\times$ month are included. Standard errors clustered at the municipality level. The point estimates represent the effect of the treatment post-intervention. Top panel report the coefficients in the municipalities were mayors received the list. Bottom panel show the results for municipalities that did not received the list. The bottom labels specify the *Letter* treatment *Investigative Journalist*, or *No CC*. The outcome is the *Log(contract value)*, with non-recipients assigned a value of 0. The log transformation for the value follows Chen and Roth (2022), defining the intensive margin as $x = -1$ for non-recipients.

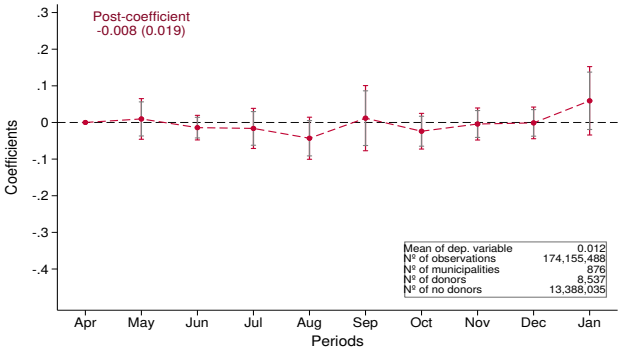
Figure B4: Effect of Inspector General Letter on donors procurement - other specifications on log(contract value)



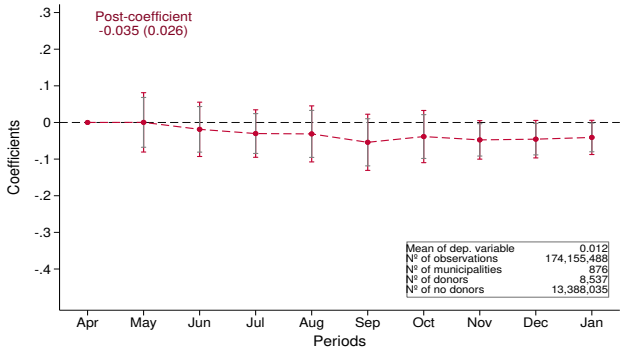
Note: The unit of analysis is the individual-month. Each panel in the figure shows point estimates and 95% confidence intervals from estimating equation 2 on procurement outcomes. Coefficients only reported for donors in the *Inspector General letter treatment arm*. Fixed effects for randomization block $\times$ $\mathbb{1}[Donor]$ $\times$ month are included. Standard errors clustered at the municipality level. The outcome is the *Log(contract value)*, with non-recipients assigned a value of 0. The log transformation for the value follows Chen and Roth (2022), defining the intensive margin as $x = -1$ for non-recipients. **Panel A** reports the effects by diving donors between those supporting the winner candidate and those supporting non-winner candidates, relative to their respective comparison in the control group. We include donor randomization block fixed effects instead of individual fixed effects for comparing donors supporting the same rank across municipalities. **Panel B** reports the effects for donors and for non-donors that were donors in previous electoral races. **Panel C** estimates the effects of donating on contract value separating the outcome by type of contract. **Panel D** estimates the effects of donating on contract value separating the outcome by value received just below the threshold of *Minimum value* contract, and just above it. Excluding the coefficients for donors in the treatment *Inspector General* + *list* and + *no list*, overall, the panels estimate a total of 40 coefficients of the effect of donating on log(contract value). From those, corresponding to the other treatment arms, only four are significant at least at the 10%.

Figure B5: Effect of RCT Letter on Procurement Efficiency – log(Overrun Value)

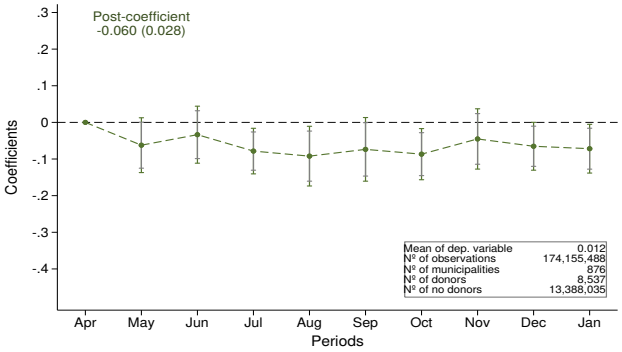
(a) Journalist - List treatments



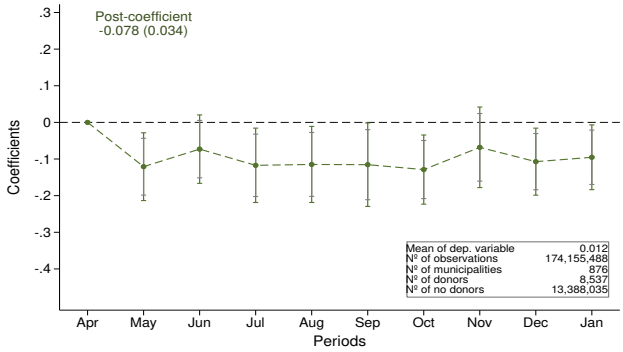
(b) Journalist - No list treatments



(c) No CC - List treatments



(d) No CC - No list treatments



Notes: The unit of analysis is the individual-month, estimating equation 2 on the overrun value. *Investigative Journalist* is for the treatment letter carbon copying investigative journalist. *No CC* is for municipalities receiving the treatment letter without carbon copy additional organizations. *No list* is for treatment letters not including the donor list as attachment. *List* group the treatment letter including the full and partial list of donors as attachment. The outcome *log(overrun value)* is the value of overrun. The log transformation follows Chen and Roth (2022) and define the intensive margin as $x = -1$ for non-recipients.

Table B7: Effect of RCT Letter on Municipal Procurement Outcomes

Dep. Variable	Log(contract value)	
	(1)	(2)
A. Inspector General×Post	-0.032	
	(0.082)	
Inspector General + no list×Post		-0.062
		(0.093)
Inspector General + list×Post		-0.002
		(0.103)
B. Investigative Journalist×Post	-0.036	
	(0.087)	
Investigative Journalist + no list×Post		0.040
		(0.092)
Investigative Journalist + list×Post		-0.112
		(0.118)
C. No CC×Post	0.113	
	(0.085)	
No CC + no list×Post		0.100
		(0.111)
No CC + list×Post		0.125
		(0.092)
Linear comb. P-values		
A. Inspector General - B. Investigative Journalist	0.957	
A. Inspector General - C. No CC	0.060	
Inspector General + list - Inspector General + no list		0.570
Inspector General + list - Investigative Journalist + list		0.388
Inspector General + list - No CC + list		0.225
Mean of dependent variable	2424.079	2424.079
Number of obs.	11,388	11,388
Number of municipalities	876	876
Municipality FE	Yes	Yes
Block × Time FE	Yes	Yes

Notes: The unit of analysis is the municipality-month, estimating equation 2 on procurement outcomes. *Inspector General* is for the treatment letter carbon copying the relevant public office that oversight public procurement. *Investigative Journalist* is for the treatment letter carbon copying investigative journalist. *No CC* is for municipalities receiving the treatment letter without carbon copy additional organizations. *No list* is for treatment letters not including the donor list as attachment. *List* group the treatment letter including the full and partial list of donors as attachment. *Pr(contract)* equals 1 if the individual received a contract in t, 0 otherwise. *log(contract value)* is the value of contracts received. The log transformation follows Chen and Roth (2022) and define the intensive margin as $x = -1$ for non-recipients. *Post* equal 1 for periods after the letter were sent to mayors. The mean of the outcomes is measured in the pre-period and is reported in million COP for the contract value. *Municipality FE* is for municipal fixed effects. *Block × Time FE* is for randomization block by month fixed effects. Standard errors clustered at the municipal level are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C A Model of Political Donations and Public Procurement

C.1 Equations

C.1.1 Expected Value Functions by Firms' State

$$\mathbb{E}_{\varepsilon_{i,T-1}}\left[V^{OO}_{T-1}(s_{T-1},\varepsilon_{i,T-1}) \mid s_{T-1}\right] = \pi^{OO}_{T-1}(s_{T-1}) + \rho\left\{\gamma + \ln\left[\exp(0) + \exp\left(\frac{\phi^{OO} + \beta\mathbb{E}[V^{OO}_{T}(s_T) \mid s_{T-1}]}{\rho}\right) + \exp\left(\frac{\phi^{OD} + \beta\mathbb{E}[V^{OD}_{T}(s_T) \mid s_{T-1}] - \kappa}{\rho}\right)\right]\right\}$$

$$\mathbb{E}_{\varepsilon_{i,T-1}}\left[V^{OD}_{T-1}(s_{T-1},\varepsilon_{i,T-1}) \mid s_{T-1}\right] = \pi^{OD}_{T-1}(s_{T-1}) + \rho\left\{\gamma + \ln\left[\exp(0) + \exp\left(\frac{\phi^{OD} + \beta\mathbb{E}[V^{OD}_{T}(s_T) \mid s_{T-1}]}{\rho}\right)\right]\right\}$$

$$\mathbb{E}_{\varepsilon_{i,T-1}}\left[V^{DO}_{T-1}(s_{T-1},\varepsilon_{i,T-1}) \mid s_{T-1}\right] = \pi^{DO}_{T-1}(s_{T-1}) + \rho\left\{\gamma + \ln\left[\exp(0) + \exp\left(\frac{\phi^{DO} + \beta\mathbb{E}[V^{DO}_{T}(s_T) \mid s_{T-1}]}{\rho}\right) + \exp\left(\frac{\phi^{DD} + \beta\mathbb{E}[V^{DD}_{T}(s_T) \mid s_{T-1}] - \kappa}{\rho}\right)\right]\right\}$$

$$\mathbb{E}_{\varepsilon_{i,T-1}}\left[V^{DD}_{T-1}(s_{T-1},\varepsilon_{i,T-1}) \mid s_{T-1}\right] = \pi^{DD}_{T-1}(s_{T-1}) + \rho\left\{\gamma + \ln\left[\exp(0) + \exp\left(\frac{\phi^{DD} + \beta\mathbb{E}[V^{DD}_{T}(s_T) \mid s_{T-1}]}{\rho}\right)\right]\right\}$$

C.1.2 Likelihood Function by Firms' State

Incumbent firm in state $s_{i,t} = OO$ The contribution in year t to the likelihood is:

$$f^{OO}(a_{i,t}|s_t;\phi^{OO},\phi^{OD},\kappa,\rho) = \Pr(a_{i,t} = \text{exit})^{\mathbb{1}(a_{i,t}=\text{exit})} \times \Pr(a_{i,t} = \text{stay})^{\mathbb{1}(a_{i,t}=\text{stay})} \times \Pr(a_{i,t} = \text{stay, donate})^{\mathbb{1}(a_{i,t}=\text{stay, donate})}$$

The probabilities of each action are given by:

$$\Pr(a_{it} = \text{exit}) = \frac{1}{1 + \exp\left(\frac{\phi^{OO} + \beta E_\varepsilon V^{OO}_{t+1}(s_{t+1})}{\rho}\right) + \exp\left(\frac{\phi^{OD} + \beta E_\varepsilon V^{OD}_{t+1}(s_{t+1}) - \delta^t\kappa}{\rho}\right)}$$

$$\Pr(a_{it} = \text{stay}) = \frac{\exp\left(\frac{\phi^{OO} + \beta E_\varepsilon V^{OO}_{t+1}(s_{t+1})}{\rho}\right)}{1 + \exp\left(\frac{\phi^{OO} + \beta E_\varepsilon V^{OO}_{t+1}(s_{t+1})}{\rho}\right) + \exp\left(\frac{\phi^{OD} + \beta E_\varepsilon V^{OD}_{t+1}(s_{t+1}) - \delta^t\kappa}{\rho}\right)}$$

$$\Pr(a_{it} = \text{stay, donate}) = \frac{\exp\left(\frac{\phi + \beta E_\varepsilon V^{OD}_{t+1}(s_{t+1}) - \delta^t\kappa}{\rho}\right)}{1 + \exp\left(\frac{\phi^{OO} + \beta E_\varepsilon V^{OO}_{t+1}(s_{t+1})}{\rho}\right) + \exp\left(\frac{\phi^{OD} + \beta E_\varepsilon V^{OD}_{t+1}(s_{t+1}) - \delta^t\kappa}{\rho}\right)}$$

Incumbent firm in state $s_{i,t} = DO$ The contribution in year t to the likelihood is:

$$f^{DO}(a_{i,t}|s_t;\phi^{DO},\phi^{DD},\kappa,\rho) = \Pr(a_{i,t} = \text{exit})^{\mathbb{1}(a_{i,t}=\text{exit})} \times \Pr(a_{i,t} = \text{stay})^{\mathbb{1}(a_{i,t}=\text{stay})} \times \Pr(a_{i,t} = \text{stay, donate})^{\mathbb{1}(a_{i,t}=\text{stay, donate})}$$

The probabilities of each action are given by:

$$\Pr(a_{it} = \text{exit}) = \frac{1}{1 + \exp\Big(\frac{\phi^{DO} + \beta E_\varepsilon V_{t+1}^{DO}(s_{t+1})}{\rho}\Big) + \exp\Big(\frac{\phi^{DD} + \beta E_\varepsilon V_{t+1}^{DD}(s_{t+1}) - \delta^t \kappa}{\rho}\Big)}$$

$$\Pr(a_{it} = \text{stay}) = \frac{\exp\Big(\frac{\phi^{DO} + \beta E_\varepsilon V_{t+1}^{DO}(s_{t+1})}{\rho}\Big)}{1 + \exp\Big(\frac{\phi^{DO} + \beta E_\varepsilon V_{t+1}^{DO}(s_{t+1})}{\rho}\Big) + \exp\Big(\frac{\phi^{DD} + \beta E_\varepsilon V_{t+1}^{DD}(s_{t+1}) - \delta^t \kappa}{\rho}\Big)}$$

$$\Pr(a_{it} = \text{stay, donate}) = \frac{\exp\Big(\frac{\phi + \beta E_\varepsilon V_{t+1}^{DD}(s_{t+1}) - \delta^t \kappa}{\rho}\Big)}{1 + \exp\Big(\frac{\phi^{DO} + \beta E_\varepsilon V_{t+1}^{DO}(s_{t+1})}{\rho}\Big) + \exp\Big(\frac{\phi^{DD} + \beta E_\varepsilon V_{t+1}^{DD}(s_{t+1}) - \delta^t \kappa}{\rho}\Big)}$$

Incumbent firm in state $s_{i,t} = OD$ The contribution in year t to the likelihood is:

$$g^{OD}(a_{i,t}|s_t;\phi^{OD},\rho) = \Pr(a_{i,t} = \text{exit})^{\mathbb{1}(a_{i,t}=\text{exit})} \times \Pr(a_{i,t} = \text{stay})^{\mathbb{1}(a_{i,t}=\text{stay})}$$

The probabilities of each action are given by:

$$\Pr(a_{it} = \text{exit}) = \frac{1}{1 + \exp\Big(\frac{\phi^{OD} + \beta E_\varepsilon V_{t+1}^{OD}(s_{t+1})}{\rho}\Big)}$$

$$\Pr(a_{it} = \text{stay}) = \frac{\exp\Big(\frac{\phi^{OD} + \beta E_\varepsilon V_{t+1}^{OD}(s_{t+1})}{\rho}\Big)}{1 + \exp\Big(\frac{\phi^{OD} + \beta E_\varepsilon V_{t+1}^{OD}(s_{t+1})}{\rho}\Big)}$$

Incumbent firm in state $s_{i,t} = DD$ The contribution in year t to the likelihood is:

$$g^{DD}(a_{i,t}|s_t;\phi^{DD},\rho) = \Pr(a_{i,t} = \text{exit})^{\mathbb{1}(a_{i,t}=\text{exit})} \times \Pr(a_{i,t} = \text{stay})^{\mathbb{1}(a_{i,t}=\text{stay})}$$

The probabilities of each action are given by:

$$\Pr(a_{it} = \text{exit}) = \frac{1}{1 + \exp\Big(\frac{\phi^{DD} + \beta E_\varepsilon V_{t+1}^{DD}(s_{t+1})}{\rho}\Big)}$$

$$\Pr(a_{it} = \text{stay}) = \frac{\exp\Big(\frac{\phi^{OD} + \beta E_\varepsilon V_{t+1}^{OD}(s_{t+1})}{\rho}\Big)}{1 + \exp\Big(\frac{\phi^{DD} + \beta E_\varepsilon V_{t+1}^{DD}(s_{t+1})}{\rho}\Big)}$$

C.2 Modified Cournot Competition Stage

We propose a minimal modification to our baseline model that allow donations to create value through access to less crowded competition, rather than through a pure marginal cost advantage. We introduce competition intensity multipliers $\theta_s \in (0,1]$ for each group $s \in \{OO, OD, DO, DD\}$. The modified first-order condition becomes:

$$P_t + \theta_s \, q_{it} \, \frac{\partial P_t}{\partial Q_t} = mc_t^s.$$

where $\theta_s = 1$ reproduces standard Cournot, while $\theta_s < 1$ means a "softer" residual demand slope (thinner competition). We allow θ to vary with the share of donors and with time. A simple parametrization is:

$$\theta_t = \sigma\left(\gamma_0 + \gamma_1 t + \gamma_2 \frac{N^{DD} + N^{OD}}{N}\right),$$

where $\sigma(x) = \frac{1}{1+e^{-x}}$ is a logit function.

Microfoundation A firm i secures a protected share $\tau_i \in [0,1)$ of its period sales through base contracts (priority awards, framework agreements, preferred supplier lists, etc.). These contracted units are priced off an exogenous index for the period and are therefore insulated from the intra-period price impact of total quantity Q_t. The remaining share $1-\tau_i$ is sold at the market-clearing price $P(Q)$. The base-contract price $\bar{P}_t$ is tied to the same public index that also determines P_t. It is set ex-ante, so $\partial \bar{P}_t / \partial q_i = 0$, but ex-post coincides with the price observed in the data. Thus, the market has one observed price, but firms treat the base-contract component as locally insensitive to their own quantity.

The firm solves:

$$\max_{q_i \geq 0} \ \tau_i \bar{P}_t q_i + (1-\tau_i) P(Q) q_i - C_i(q_i)$$

. The first-order condition is with respect to q_i is

$$\tau_i \bar{P}_t + (1-\tau_i)\big[P(Q) + q_i P'(Q)\big] = C_i'(q_i).$$

Since $\bar{P}_t = P(Q)$ in levels:

$$P(Q) + (1-\tau_i) q_i P'(Q) = mc_i.$$

Which reveals that the conduct parameter is:

$$\theta_i = 1 - \tau_i.$$

The interpretation is straightforward: the fraction τ_i of the firm's sales is shielded from the price externality, so the firm internalizes only the residual slope of the demand curve corresponding to the uncovered share $1-\tau_i$. In practice, one can implement this by assigning group-specific contract shares $\tau_{\text{donor}} > 0$ and non-donors $\tau_{\text{non}} = 0$. Then

$$\theta_g = 1 - \tau_g$$

gives group-specific conduct parameters. This provides a clean microfoundation for θ.

C.3 Welfare Calculation

Government welfare (buyer surplus) in each period is:

$$GS_t = \frac{1}{\alpha}\left[\ln\left(\sum_j e^{\bar{U}_{jt}}\right)\right] - \sum_j p_{jt} Q_{jt}$$

where the deterministic component of the mayor's utility when contracting with firm j is $\bar{U}_{jt} = \xi_j + \tau_t + \beta' x_{jt} - \alpha p_{jt}$ and α is the demand price coefficient. The first term captures the expected utility of discretionary awards (Small-Rosen inclusive value), while the second subtracts procurement expenditures. Firm surplus is the sum of Cournot profits:

$$\Pi_t = \sum_i (P_t - mc_{it}) q_{it},$$

where mc_{it} are marginal costs recovered from the Cournot first-order conditions. Total resource costs include real resource expenditures from donating, entry, and operation:

$$\begin{aligned} RC_t = &(\text{Estimated sunk cost of donation}) \times (\text{Number of donors}_t) \\ &+ \sum_{\text{states}} (\text{Fringe cost of type } s) \times (\text{Number of firms of type } s_t) \\ &+ (\text{Estimated entry cost}_t) \times (\text{Number of entrants}_t) \end{aligned}$$

The aggregate discounted welfare under the baseline is:

$$W = \sum_{t=0}^{T} \beta^t \left[GS_t + \Pi_t - RC_t \right]$$

Simulation and Welfare Decomposition For each counterfactual c, we simulate 10 thousand equilibrium paths of market evolution $\{s_t^{(m,c)}\}_{t=0}^{T}$ using the corresponding policy functions. At each simulated period we compute each welfare component. Averaging across simulations gives:

$$E[GS_t^{(c)}] = \frac{1}{M} \sum_{m=1}^{M} GS_t^{(m,c)} \qquad E[\Pi_t^{(c)}] = \frac{1}{M} \sum_{m=1}^{M} \Pi_t^{(m,c)} \qquad E[RC_t^{(c)}] = \frac{1}{M} \sum_{m=1}^{M} RC_t^{(m,c)}$$

Aggregate discounted welfare under counterfactual c is:

$$W^{(c)} = \sum_t \beta^t \left(E[GS_t^{(c)}] + E[\Pi_t^{(c)}] - E[RC_t^{(c)}] \right).$$

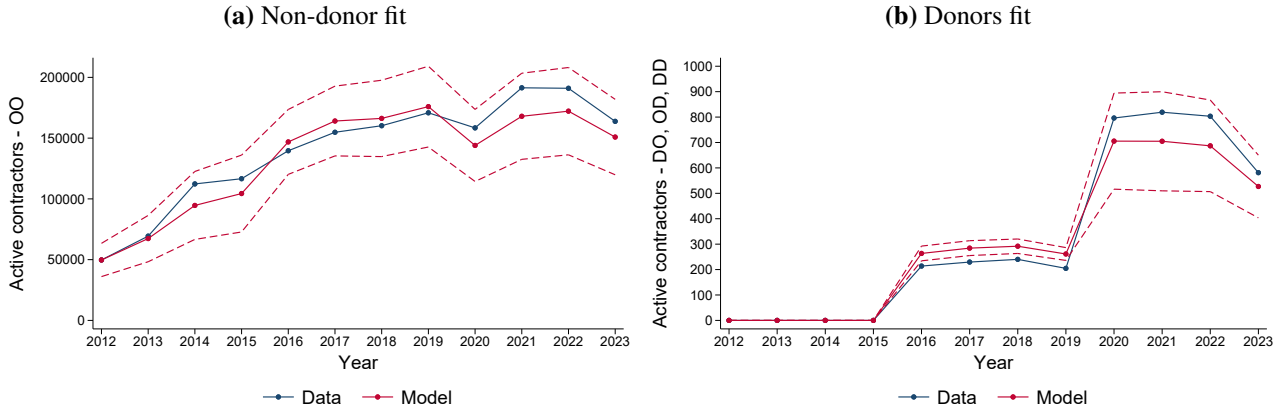
Welfare differences relative to the baseline are defined as $\Delta W^{(c)} = W^{(c)} - W^{baseline}$, or the sum of the differences for each welfare component:

$$\Delta W^{(c)} = \sum_t \beta^t \left[\Delta GS_t^{(c)} + \Delta \Pi_t^{(c)} - \Delta RC_t^{(c)} \right],$$

where $\Delta GS_t^{(c)}$ is efficiency in contract allocation through prices/quantities, $\Delta \Pi_t^{(c)}$: firm-selection and competition effects, $\Delta RC_t^{(c)}$ is resource-cost effects through donation and entry

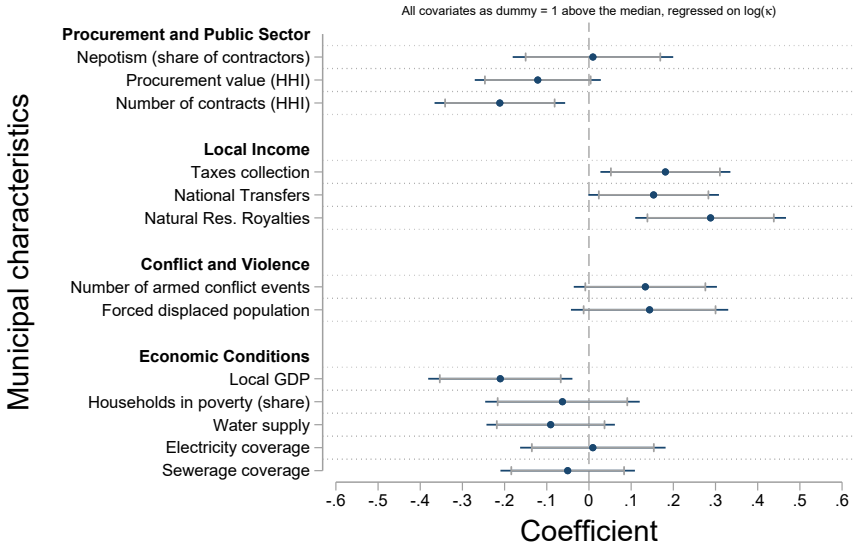
C.4 Additional results

Figure C1: Model fit to observed data - entry patterns



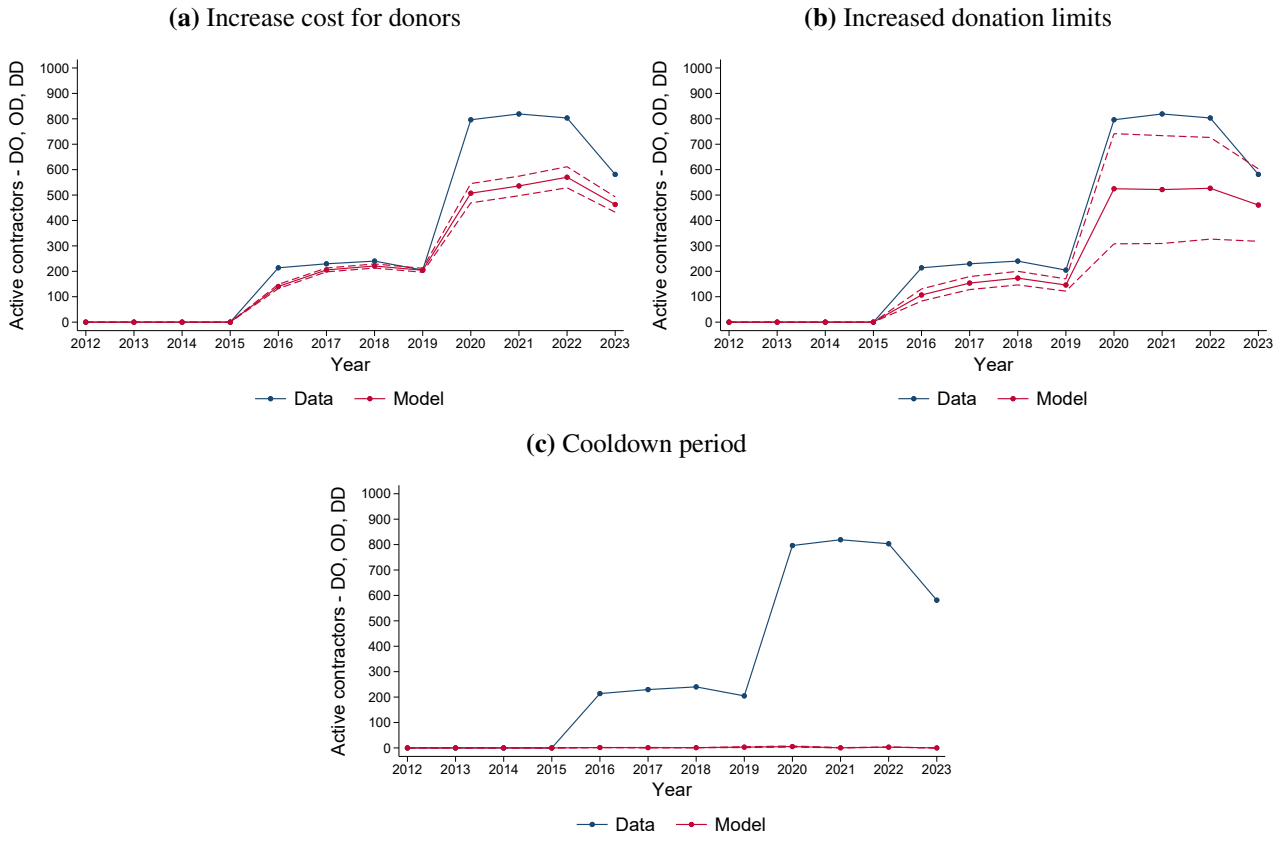
Note: The figure illustrates the overall entry for donors and non-donors implied from the estimated model (in red), its 95% confidence interval (dashed red line), and the observed data (in blue). Implied entry consist in the sum of the estimated entries by municipality-year. For each municipality, we obtain the estimated entries as the average over 10 thousand bootstrap simulations. Donor fir include donation states (OD, DD) and non-donors that donated before (DO).

Figure C2: Correlation between Sunk Cost of Donating and Municipal Covariates



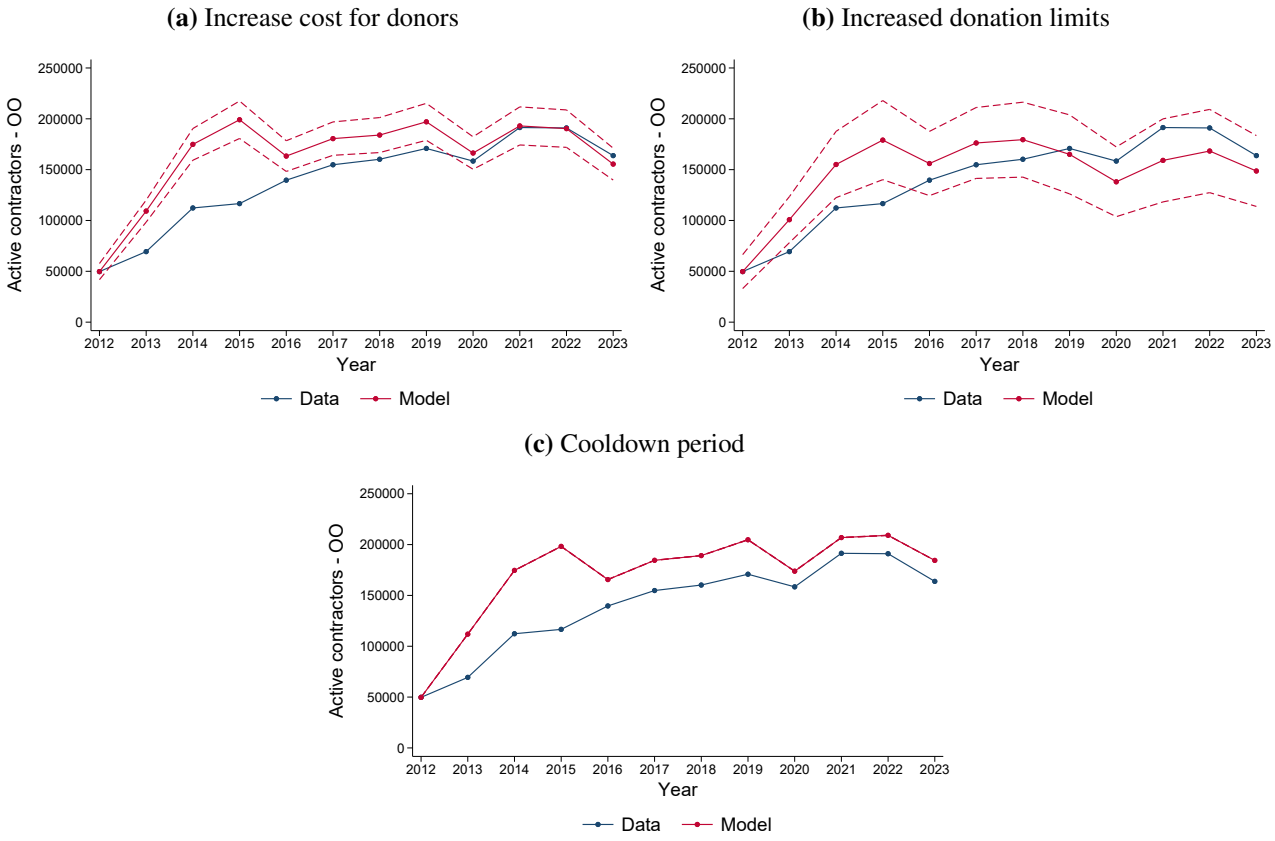
Note: The figure plots the coefficient point and the 95% (90%) confidence intervals of regressing each municipal covariate (displayed in the y-axis) on the log(κ) estimated from the structural model. The covariates are measured as dummy variables equal to one if the municipality is above the median of the distribution among all municipalities for which the parameter κ was estimated. Data of share of contractors with nepotistic ties comes from Riaño (2021). Market concentration (HHI) in procurement value and number of contracts was measured using dat from SECOP. Municipal characteristics on local income, conflict and violence, and local economic conditions were recovered from the Panel CEDE from Universidad de los Andes. The regression include department fixed effects and robust standard errors.

Figure C3: Counterfactual policies: changes in entry decisions for donors



Note: The figure plots the entries for non-donors in the base model (blue) and counterfactual policies (red). Panel (a) show the result from a policy banning the entry to the procurement system to donors. The policy is implemented by estimating the model using the optimal parameters and replacing κ by $\kappa \times 5$. Panel (b) show the results for decreasing the sunk cost of donation (allowing more legal donations). The policy is implemented by estimating the model using the optimal parameters and replacing κ by $\frac{\kappa}{5}$. Panel (c) implements a cooldown policy, consisting in forbidding the entry to the procurement system to donors during two years after adoption. The policy is implemented by estimating the optimal model including a constrain in which donors are not allowed to entry until two periods after adoption.

Figure C4: Counterfactual policies: changes in entry decisions for non-donors



Note: The figure plots the entries for agents not donating from the base model (blue) and counterfactual policies (red). Panel (a) show the result from a policy banning the entry to the procurement system to donors. The policy is implemented by estimating the model using the optimal parameters and replacing κ by $\kappa \times 5$. Panel (b) show the results for decreasing the sunk cost of donation (allowing more legal donations). The policy is implemented by estimating the model using the optimal parameters and replacing κ by $\frac{\kappa}{5}$. Panel (c) implements a cooldown policy, consisting in forbidding the entry to the procurement system to donors during two years after adoption. The policy is implemented by estimating the optimal model including a constrain in which donors are not allowed to entry until two periods after adoption.