Corporate Dark Money in Politics: Evidence from India

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This paper examines corporate dark money in politics using a novel regulatory episode in India. From 2018 onward, firms could make confidential, unlimited donations to political parties via "electoral bonds." A 2024 Supreme Court ruling banned the practice and retroactively disclosed all $2 billion of such donations. Linking these data to a newly assembled dataset of publicly disclosed contributions going back to 2003, we establish that confidential donations differ markedly from disclosed ones: they are far larger in aggregate, attract bigger and more sophisticated firms, and frequently link donor firms to multiple political parties–a pattern absent from disclosed giving. When confidentiality is unexpectedly removed, publicly listed donor firms experience significant negative abnormal returns, implying an estimated $12 billion in value destruction–over five times total funds raised through electoral bonds. These patterns are consistent with dark money fostering political hedging while minimizing the risk of political retribution for donor firms. Three further findings support this interpretation: Firms hedge more broadly across parties and especially around closely contested elections when donating confidentially; sophisticated firms disproportionately shift from disclosed to confidential channels; and the market penalty upon disclosure falls hardest on firms with opposition-party ties. Paradoxically, the creation of a hidden donation channel may foster political plurality by lowering the cost of donating to opposition parties.

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1. Introduction

Political donations, as well as their determinants and effects, have been extensively studied. Virtually all work in this literature relies on publicly disclosed donations due to data availability constraints. However, publicly disclosed donations are likely just the tip of the iceberg, and may systematically differ from confidential ones.[1] In many countries, legal "dark money" channels allow corporations or high net worth individuals to fund political campaigns outside public view.[2] Understanding the role of dark money in politics is therefore crucial to political economy, and of growing importance given recent legal and technological developments, such as the rise of Super PACs in the US, or the growth of the crypto-currency ecosystem. Donation opacity is also of particular interest in developing countries, where illegal (and therefore undisclosed) donations might be more frequent and even legal donations whose disclosure are mandatory may remain hidden because of weak enforcement of disclosure rules or inadequate data collection.

Understanding the role of dark money in politics raises two core empirical challenges: a measurement one and a counterfactual one. First, while scholars have taken forensic approaches to uncover hidden corporate-political links—e.g. via philanthropic giving (Bertrand et al. 2020), biographical connections (Bertrand et al. 2018), local commodity price distortions around elections (Sukhtankar 2012), and even sudden deaths of known donors (Battaglini et al. 2024)—these approaches offer at best a partial and noisy picture of the phenomenon. Second, without an unexpected introduction of a confidential channel accompanied by comprehensive data on disclosed donations before and after the reform, as well as on confidential donations themselves, it is difficult to study how a dark money channel affects overall political giving.

This paper addresses these two challenges by leveraging a novel regulatory sequence in India –the world's largest democracy, where elections are among the most expensive in the world and corporate funding is particularly salient (Kapur and Vaishnav 2018). From 2003 onward, corporations in India could only make political donations through publicly disclosed channels, reported by political parties in annual contribution reports. In 2017, the government introduced a new confidential channel for corporate donations via "electoral bonds."[3] Donors could purchase them in fixed denominations and deposit them in political parties' accounts at specific branches of the State Bank of India. These donations were completely unobservable by the public, the media, or non-recipient political parties, and unlimited in amount. In February 2024, however, a Supreme Court ruling forced the government to reverse course and retroactively disclose granular details of all confidential political contributions. By compiling these data and linking

[1] See for instance, Wood (2018); Bombardini and Trebbi (2020); Denes et al. (2022); Bombardini and Trebbi (2025). Battaglini et al. (2024) suggests this might be an explanation for the puzzle about why there is so *little* money in politics despite the large economic stakes (Ansolabehere et al. 2003).

[2] Sometimes called "opaque" or "hidden" or "soft" (Apollonio and Raja 2004) , or "grey" (Grumbach and Pierson 2019), or "veiled" (Garrett and Smith 2005), these are all terms for political giving that is difficult to trace and quantify, which is the focus of this study.

[3] Despite their name, electoral bonds are not bonds but vouchers that may be deposited in party bank accounts.

them to a newly assembled dataset of publicly disclosed contributions since 2003 as well as administrative data on Indian corporations, we document the nature and scope of corporate dark money in the financing of political campaigns.

More specifically, this study tackles the following research questions: How does opacity affect corporate political donations? How do confidential donations differ from *disclosed* ones? Who values confidentiality when making political donations and what does it reveal about their motives? What is the value of such confidentiality?

We first provide four novel empirical facts that speak to these questions. First, once a confidential donation channel is opened for corporations, the total amount of donations rises sharply, and confidential donations dwarf disclosed ones. After the introduction of e-bonds, political parties raised corporate donations at more than four times the baseline annual rate recorded over the prior decade, in real terms, with two thirds flowing through e-bonds. While some of the increase in total donation volume could result from the simultaneous removal of the donation cap, this is unlikely to be the primary driver. Since the annual donation cap was high and proportional to firm size (7.5% of annual profits), it was far from binding for virtually all donors prior to its removal, and the amount of disclosed donations only modestly increases following it, while confidential donations surge.

Second, the scope and characteristics of firms donating through the confidential channel differ significantly from those making only disclosed donations, both before and after the introduction of e-bonds, with only a small number of firms participating in both channels. Over 7,600 distinct firms made disclosed donations to political parties since 2003, and around 1,100 bought electoral bonds after their introduction, but only approximately 150 companies participated in both channels over the 2018–2024 period. Confidential donor firms tend to be significantly larger (as measured by paid-up capital), older, and more likely to be publicly listed than disclosed donors, and even more so relative to the broader population of registered firms. The average confidential donor thus has a book equity value more than four times as large as that of the average disclosed donor, and is twice as likely to be a publicly listed firms. Industry and geographic patterns also differ, with utilities companies being particularly represented among confidential donors, as well as firms from West Bengal and Telangana.

Third, when firms give to political parties confidentially, they donate more often, in greater amounts, and to a broader set of parties relative to firms donating publicly, even controlling for size. More than 90% of confidential donors make multiple donations, and a majority of them donate to multiple parties, in sharp contrast to disclosed donors. Confidential donors are also more persistent: if a firm donates in year t, the odds it donates again in year $t+1$ are 2.5 times as high through the confidential channel relative to the disclosed one (25% vs. 10%). We document these differences in both the cross-section and the time-series: previously disclosed donors change their donation patterns once they can do so without disclosure. This latter fact suggests that selection is unlikely to fully explain the cross-sectional difference.

Fourth, the revelation of confidential donations has significant market value implications for donor firms: publicly listed confidential donors suffer significant drops in market capitalization upon disclosure. In an event study around the release of the electoral bond data, we find significant negative abnormal returns for publicly listed firms revealed as confidential donors. The magnitude of the market reaction suggests high private returns to confidentiality, as the value loss is over five times the amount raised through confidential donations from all firms.[4]

These facts illustrate that the existence of a confidential channel is associated with a meaningful reshaping of campaign finance: confidential donors give more in aggregate, tend to be a different set of firms, give more frequently and to more parties, and face significant market value consequences upon disclosure. Notably, introducing a confidential donation channel may foster political plurality, as donors are more likely to donate to opposition parties when doing so anonymously. However, the significant increase in aggregate donations associated with such a channel raises concerns about corporations gaining disproportionate political influence. It also remains an open question to what extent confidential legal donations crowd out illegal ones—the stated rationale behind the electoral bond reform.

Turning to the economic mechanism underlying these facts, we hypothesize that corporations make confidential political donations to hedge politically while minimizing retribution from the ruling party. Firms wishing to donate across multiple parties face a dilemma: hedging political risk requires supporting opposition parties, but doing so visibly risks provoking retaliation from the party in power.[5] A confidential channel resolves this tension by allowing firms to pursue a diversified political strategy while shielding their donations from rival parties' scrutiny. While our previous facts are broadly consistent with this mechanism, it generates sharper predictions: multi-party donations should be more pronounced around closely contested elections, and the negative market reaction should be more pronounced for firms with opposition-party ties.

We find empirical support for this mechanism. First, when donating confidentially, firms donate more broadly across parties, and this pattern is more pronounced around closely contested state elections—precisely when political uncertainty and retribution risk are greatest. Second, the negative stock price effects upon revelation are concentrated among firms with known non-BJP affiliations and firms headquartered in states governed by opposition parties—consistent with markets pricing in heightened retribution risk for these firms. We also show that consumer-facing firms show no differential uptake of the confidential donation channel, providing little support for a reputational backlash explanation.

These findings point to a nuanced view of dark money in politics: a confidential donation

[4]Note that ex post value destruction upon revelation does not necessarily imply ex ante gains, but underscores the importance of confidentiality to donors.

[5]In India's political environment, the ruling BJP controls central investigative agencies—the Enforcement Directorate, the Central Bureau of Investigation, and the Income Tax Department—that have been used with increasing frequency since 2014.

channel may paradoxically foster political plurality.[6] Firms that want to support rival parties, whether out of a hedging motive or genuine political preference, might refrain from doing so for fear of the ruling party's investigative apparatus. A confidential channel can empower them to do so.

Literature. This paper contributes to the growing literature on dark money in politics.

While anecdotal and journalistic accounts of confidential campaign finance abound (Mayer 2016), academic treatment has remained more limited, making the normative case for transparency (Wood 2018; Bebchuk et al. 2020), or studying strategic disclosure theoretically (Schnakenberg and Turner 2025; Jia et al. 2023). Recent work attempts to estimate the extent of undisclosed contributions by tracing more obscure channels of spending (Denes et al. 2022; Bombardini and Trebbi 2025), but in general empirical visibility into firm-level participation in dark money channels remains rare. We exploit a unique disclosure event in India to provide the first comprehensive account of confidential corporate giving in a major non-U.S. democracy, offering new insight into the scale, rationale, and participants in dark money systems.

Bringing novel administrative data, this paper makes a further empirical contribution in two ways: covering an emerging economy, and studying a broad set of corporations. Alongside Puri (2024) for India, Boas et al. (2014); Avis et al. (2022) for Brazil and Gulzar et al. (2022) for Colombia, this paper is one of the first systematic studies of campaign finance in a non-OECD country. Existing research on corporate-political links in India has so far been more conceptual in nature (Kohli 2012; Jaffrelot et al. 2019), and empirical studies tend to take a more investigative approach—examining commodity prices around election times (Sukhtankar 2012; Kapur and Vaishnav 2013) or combing through newspaper reports for corporate-political co-presence (Chen et al. 2025). Second, by using comprehensive administrative data on all firms in the formal sector, this paper moves beyond inherent limitations in the literature on corporate politics that only studies large publicly held companies due to data availability.

This study connects with a rich literature examining the value of political connections for firms through stock price event studies conducted around political shocks, including the death of a patron (Fisman 2001), political appointments (Acemoglu et al. 2016), election turnover (Wagner et al. 2018), and coups (Dube et al. 2011). It relates to Werner (2017) and Minefee et al. (2021), who exploit accidental disclosures of corporate donors to Republican-associated nonprofits, and parallels work in finance on surprise corruption disclosures and firm performance (Colonnelli and Prem 2022; Colonnelli et al. 2022).

More broadly, this study contributes to a growing literature on the costs of corporate political activity. Bertrand et al. (2018) and Akcigit et al. (2023) show how political connections can distort firms' operations through electoral pressure or reduced innovation incentives. Negative attitudes toward revealed corporate political activity can take a toll on firm performance (Borisov

[6] Given that e-bonds were introduced by the ruling BJP, this consequence may not have been anticipated by its architects.

et al. 2016; Katic and Hillman 2023): companies' sales may suffer once consumers learn about and disagree with their political leanings (Panagopoulos et al. 2020; Bhandari 2022; Conway and Boxell 2024). In a conjoint experiment, Kubinec et al. (2021) finds that potential political connections dissuade hypothetical investors. This paper identifies how a confidential donation channel allows firms to navigate this trade-off, and studies its political economy implications. The hedging motive we document connects to Hassan et al. (2019), who show that firms facing higher political risk are more likely to spread donations across parties—a pattern we find amplified when firms can do so confidentially.

Finally, in showing how dark money can foster financial support for opposition parties, this paper provides empirical grounding for recent theoretical work on the political consequences of campaign finance opacity. Schnakenberg and Turner (2025) model how the availability of dark money alters the equilibrium of campaign spending by allowing donors to secretly offset the electoral costs of their public contributions. Our findings offer a real-world counterpart: when Indian firms could donate confidentially, they directed a larger share of contributions to opposition parties, particularly around closely contested elections. Our findings suggest, therefore, that dark money may paradoxically increase electoral competition.

2. Corporate Political Donations in India: Background and Data

2.1. Institutional background and regulatory timeline

This section provides a short overview of campaign financing and its recent evolution in India.[7]

India is a federalized parliamentary democracy with competition between multiple political parties at both the national and state levels. Despite operating single member districts with first-past-the-post electoral (FPTP) systems, where citizens vote for members of parliament and members of state assemblies directly, political parties tend to hold primacy over individual politicians. This situation is comparable to the US and in contrast to other settings, like Brazil, where candidates dominate party affiliation, and partly as a result of a 1980s anti-defection law where party members are barred from voting against the party whip (**?**). As a result, political financing is enshrined legally at the party level. India has a long history of corporate financing of politics. Even before independence, industrialists such as G.D. Birla were key funders of the Indian National Congress. In the early post-independence years, the dominant Congress Party exchanged regulatory permissions and licenses for financial support from business houses (Kochanek 1974). While such corporate donations were legal under the 1956 Companies Act, Prime Minister Indira Gandhi's 1969 banned corporate contributions (without replacing them with public financing mechanisms). Such legal decision moved corporate donations underground into an era of "briefcase politics" (Kochanek 1987).

[7]This is a summary that draws on more detailed accounts available in Sridharan (1999); Gowda and Sridharan (2012); Kapur and Vaishnav (2018); Jaffrelot et al. (2019).

India's liberalization in the 1980s and 1990s catalyzed changes in party finance law. In 1985, corporate donations were re-legalized but capped at 5% of the three-year trailing average of net profits, subject to board approval and disclosure in financial statements. This cap was raised to 7.5% in 2012. A key turning point for transparency came in the 2000s, when the 2005 Right to Information (RTI) Act passed, empowering citizens to petition for data. In 2008, the NGO Association for Democratic Reforms (ADR) successfully used the RTI to compel disclosure of all political contributions above INR 20,000, retroactively applicable to 2003. The Election Commission of India (ECI) now publishes these financial disclosures online, and ADR transcribes them into searchable formats. These reforms also incentivized a shift to legality: in 2003, corporate and individual donations became fully tax deductible; and in 2012, the creation of Electoral Trusts allowed corporations to pool and distribute funds transparently under ECI oversight.

On February 1st, 2017, the ruling BJP party announced a number of changes to the campaign finance landscape in 2017 Finance Bill presented to parliament. First, it removed the cap on corporate donations, and dropped the requirement to disclose party contributions in companies' annual reports. Still, political parties were required to disclose any donations above INR 20,000 (ca. USD300). Second, it introduced a new Electoral Bond Scheme as an alternate mechanism for party financing. In this scheme, individuals or companies could purchase bearer bonds of different denominations, and deposit them into the accounts of political parties at the State Bank of India (SBI), on a set of pre-specified days in a year. These donations would retain their tax advantage, but incurred no disclosure requirement. While the government justified this opacity as necessary to curb "black money,"[8] critics argued that it merely legalized secrecy (Vaishnav 2019).[9]

Starting January 2018, companies could choose whether to make donations to parties that would be disclosed if above INR 20,000 (a high amount for individuals, but not for formally registered businesses), or whether to make confidential deposits of electoral bonds in party bank accounts. After over a year without any tracking, starting in April 2019, the Supreme Court modified the scheme to ensure the State Bank of India would collect the details of these electoral bond purchasers and share them with the ECI, which would then produce annual reports of aggregate fundraising.

After the electoral bond scheme was announced, the civil society organization "Association for Democratic Reform" challenged the legality of the scheme. In October 2023, the Supreme Court heard oral arguments, and on February 15, 2024 –against popular expectations– the Court struck down the scheme as unconstitutional and required the names of all donors to be published on the ECI's website by March 6. After a small delay, on March 12, SBI submitted two lists to

[8]"Black money" was top of the national political agenda at the time. In 2014 the BJP had been voted in on the back of an anti-corruption swing against the INC-run coalition, and in 2016 the BJP waged an attack on "black money" in the economy by demonetizing 86% of currency bills in circulation overnight, with major macroeconomic consequences (Lahiri 2020; Chodorow-Reich et al. 2020).

[9]Legal details about the Electoral Bond Scheme and its timeline are documented in detail on the website of legal watchdog, Supreme Court Observer: `https://www.scobserver.in`.

the ECI: the list of bond purchases with details of the bond purchaser, and the list of deposits into party accounts.[10] On March 14, the ECI published these two lists on its website. The most glaring omission at this point was the two lists could not be combined: it was impossible to identify *which party* each donor was donating to. Upon pressure from the Supreme Court, the ECI released fresh data on March 21 with donation-specific identifiers that allowed the two lists to be linked, enabling analysts and journalists to trace firm-level political contributions with unprecedented clarity.

2.2. Data

Our data set is built from three main sources: the electoral bond registry released by the Supreme Court, the regular donation registry disclosed by the Electoral Commission of India, and administrative data on Indian corporations. We complement these main sources with a variety of data sources, including financial data from Prowess and Datastream and data on election results.

Confidential donations ("Electoral Bonds"). The main data source for this paper is the list of electoral bond purchases published on the ECI website on March 14, 2024. This list contains information about the date of purchase, name of purchaser, and denomination of bond bought, for almost 19,000 purchases, made between April 2019 and February 2024, to 26 parties, amounting to over 120 billion INR (approx. 1.7 billion USD) (Traveli and Kumar 2024).

A key challenge with this data is that electoral bond buyers are not consistently identified. For instance, the original list reports donations from `Achintya Solar Power Private Limited` and `Achintya Solar Power Pvt Ltd`, which are the same legal entity, but would be counted as distinct entities using an exact string matching procedure. Instead, we develop and use a web-scraping based entity resolution algorithm that links each corporate donor to its unique 21-digit corporate identification number (CIN), which helps resolve cases of ambiguous or duplicated entities.[11]

The CIN is available to all formally registered businesses in India. While there is no size floor to formally incorporate, it does come with onerous regulatory requirements like annual financial reporting to the Ministry of Corporate Affairs, and convening a minimum of a 2-person board of directors, which filters out smaller "mom and pop" *kirana* stores and micro enterprises which may remain informal or register for a less onerous tax ID (GSTIN) rather than full incorporation. Out of the over-1100 unique electoral bond buyers, approximately 800 are corporate donors with corporate ID numbers, making almost 97% of donation value.

[10] On March 4, SBI requested an extension until June 30—after the national elections, slated for April-May 2024. But the SC rejected this request and gave a new deadline of March 15.

[11] See Puri (2025) for details about this entity resolution algorithm, and its performance compared to standard fuzzy and probabilistic string matching techniques.

Disclosed donations. We complement the electoral bonds data with disclosed donations from parties' annual disclosure to the Election Commission of India, as recently collected and standardized in Puri (2025) and Puri (2024). In short, we scrape the database of political donations manually transcribed by the NGO ADR and published to its website `myneta.info`. We identify corporate donors bysearching for various corporate-related strings (like "private limited", etc.), and match irregularly recorded corporate donors to their consistent CIN number via the same entity-resolution algorithm described earlier. For missing CINs, we augment this automated procedure with an extensive manual process of collecting unique tax IDs (PAN numbers) recorded in the parties' annual contribution reports, and matching these tax IDs to CIN. For donations by electoral trusts to political parties, we hand collrvy all contributions made to electoral trusts each year, and fetch the corporate ID numbers.

Overall, we recover over 7,600 unique corporate entities making approximately $1.2 billion dollars in donations to 42 political parties between 2003 and 2023.

Adminstrative firm-level data. We obtain information on firm characteristics using the CIN number and associated corporate registrars from the Ministry of Corporate Affairs (MCA). The Corporate ID Number, which is the official unique identifier for firms in India, contains in itself useful firm-level characteristics. The 21-digit CIN itself encodes several useful pieces of information:

For instance, `Nalli Silk Sarees Pvt Ltd`, a purveyor of women's garments in India, has the following CIN number:

`U52100TN1993PTC025196`

This string embeds the following information:

- `U`: Listing status (company)
- `521000`: National industry code[12] (retail trade)
- `TN`: State of registration (Tamil Nadu)
- `1993`: Year of registration (1993)
- `PTC`: Company type (private limited company)
- `025196`: Company's registration number

In addition, the Ministry of Corporate Affairs (MCA) publishes the full registrar of all companies registered in India going back to 1857 on its website, with firms identified by their corporate ID number. Even though parts of a firm's CIN number may evolve as its corporate structure evolves (e.g. goes from privately held to publicly listed) or the state of registration modifies with the creation of a new state (e.g. the 2013 split between Telangana and Andhra Pradesh), the six digit registration number remains consistent and tied to a single corporate entity.

We collect this complete registrar of almost 2 million firms that comprise the formal sector of India, which helps provide a baseline to compare donors with non-donor firms. In addition,

[12]Which is harmonized with the International Standard Industrial Classification (ISIC).

this registrar provides a measure of each firm's size by reporting its paid up capital (equivalent to a company's share capital).

For a subset of companies in our data and all publicly listed companies across both the Bombay and National Stock Exchanges, we collect a richer set of financial variables recorded annually and made available via Prowess through CMIE—which collects data on over 50,000 of the largest companies in India and is commonly used in academic studies relating to Indian firms.[13] For daily stock price data, we use Datastream.

3. Stylized Facts

In this section, we leverage the unique dataset resulting from the Indian regulatory timeline to uncover a set of novel stylized facts about dark money in politics.

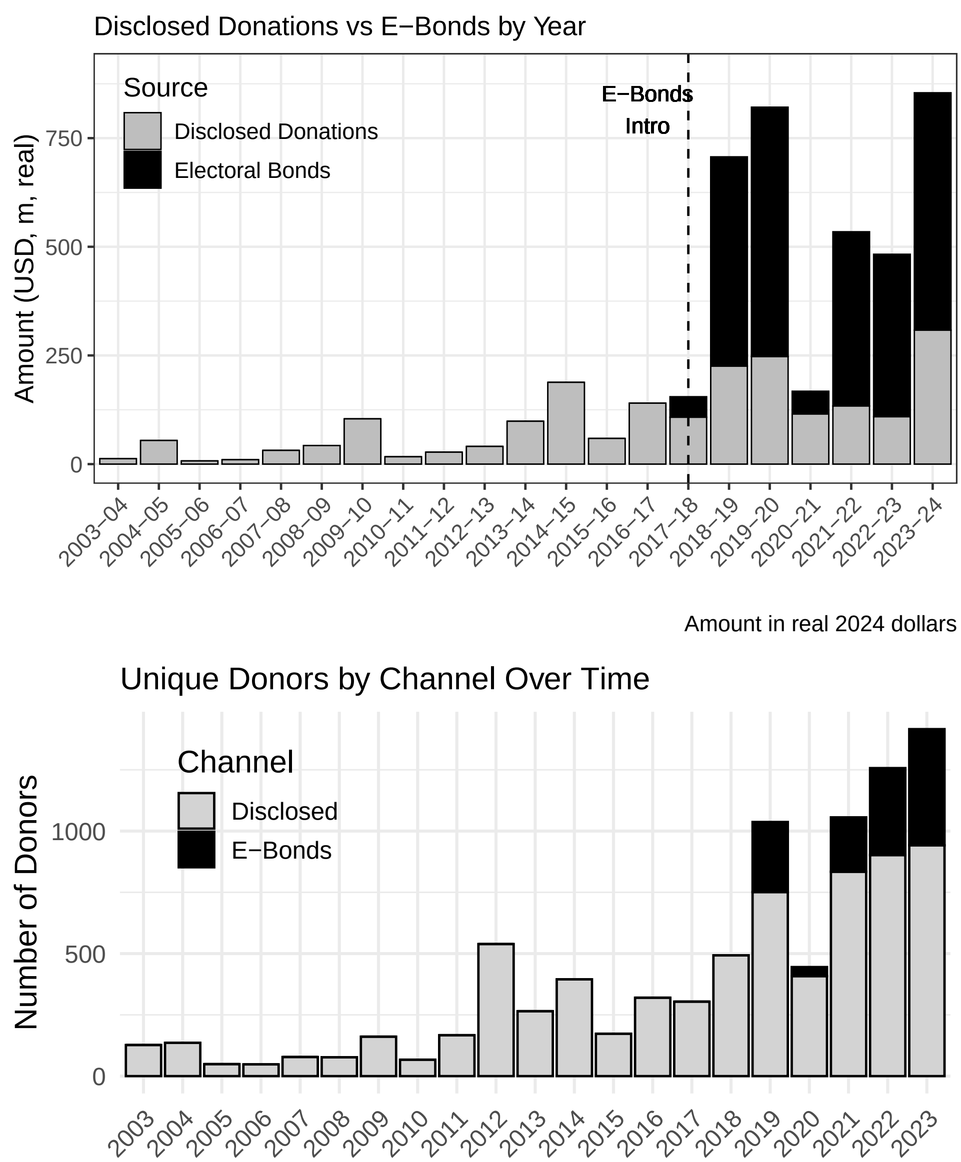
3.1. Aggregate donation volume increases sharply, driven by confidential donations

The introduction of a confidential channel for corporate donations is associated with a sharp increase in the total volume of corporate donations flowing to political parties. Panel A of Figure 1 plots the aggregate volume of donations for each channel over time. Donations tend to spike in national election years (2004, 2009, 2014, 2019). Strikingly, once a confidential channel is opened, donations through it immediately outpace those through the disclosed channel, and by a large margin. After the introduction of e-bonds, political parties raised corporate donations at more than four times the baseline annual rate recorded over the prior decade, in real terms, with two thirds flowing through e-bonds. Disclosed donations, by contrast, appear to grow at the same pace as in the pre-electoral bond period. The large amount of confidential donations come from a smaller number of donors than disclosed ones, as shown in Panel B of 1. In Figure A1 in the appendix, we also examine annual audited party expense reports. They indicate a sharp increase in aggregate expenditure by political parties in 2018, at the time of the introduction of electoral bonds.

An important consideration is whether the surge in donation total volume post-2018 could be driven by the removal of the 7.5% cap on corporate donations (as a share of trailing three-year average net profits), rather than the introduction of a confidential channel. However, two facts suggest the cap removal is unlikely to be the primary driver, although it did play a role in the large volume of confidential donations. First, the cap was removed for *both* disclosed and anonymous donations, yet disclosed donations continued on their pre-2018 trend while anonymous donations immediately reach volumes that were never reached by disclosed donations. The cap removal in itself cannot therefore explain this differential evolution. Second, prior to its removal, the cap was rarely binding. Figure 2 plots total annual donations against three-year average net profits for each company-year in which we can match donors to financial data from Prowess. The vast

[13] See for instance Bertrand et al. (2002); Goldberg et al. (2010); Kala (2024).

FIGURE 1. Party Finance By Source



Note: The top figure compares total donations by channel by fiscal year (April to March) and shows how electoral bonds far outstripped the disclosed channel as a funding source. The bottom figure counts the number of unique donors across each channel. Together, the figure shows that while electoral bond donors are few, they make outsized contributions to party coffers. Source: ADR, Author's calculations using average annual USDINR exchange rates.

majority of donations—both pre- and post-2018—fall well below the 7.5% threshold. After 2018, it is primarily electoral bond purchases that push above the cap line, not disclosed donations. This pattern is consistent with anonymity, not the removal of the cap, being the key driver of the increase in donation volume.

Figure A2 in the Appendix shows that overall corporate donors make up the bulk of political donations by year across both channels—a departure from the US case, where individual donors dominate (Ansolabehere et al. 2003). Among disclosed donations there is a censoring problem that arises from the INR 20,000 disclosure threshold. Individuals are more likely to donate below the cap, meaning their donations are less likely to be captured. For the anonymous electoral bonds, there is no such problem. Electoral bonds were sold in denominations starting at INR 1,000 (roughly $12 in 2025), but fewer than 1% of all electoral bond purchases were of the Rs 1000-denominated variety, indicating little take up by individual small donors in general. Instead, almost 97% of anonymous donations came from corporations.

3.2. Characteristics of confidential donors

We compare donors using confidential donations, i.e. electoral bond buying firms, with disclosed donor firms and the overall population of firms from the MCA's registrar of registered companies. Panels A and B in figure 3 show how donors vary compared to the overall population of firms in general, and then within the choice of donation channels.

Note that some firms within the disclosed and electoral bond categories are overlapping.

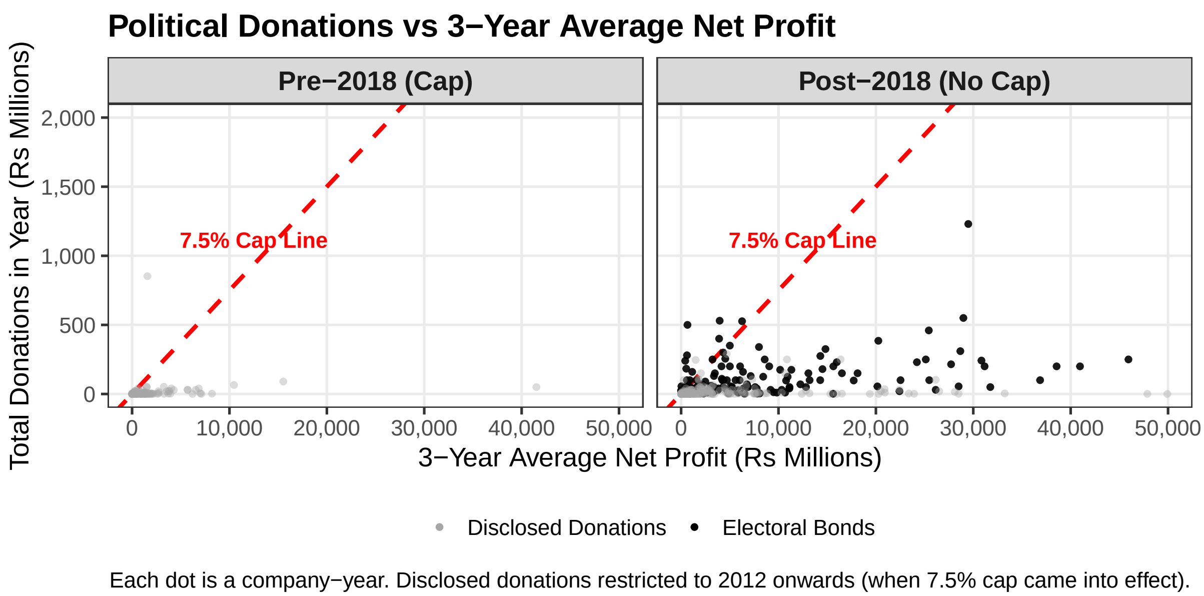
Fig 3 highlight how electoral bond buyers tend to be larger, older firms and more likely to be publicly listed corporations.

3.3. Confidential Donation Patterns and Recipients

Figure 5 captures how strikingly different firms behave when using each donation channel. While disclosed donors tend to donate once, and to a single party, electoral bond buyers tend to donate often, in larger sums, and to multiple political parties.

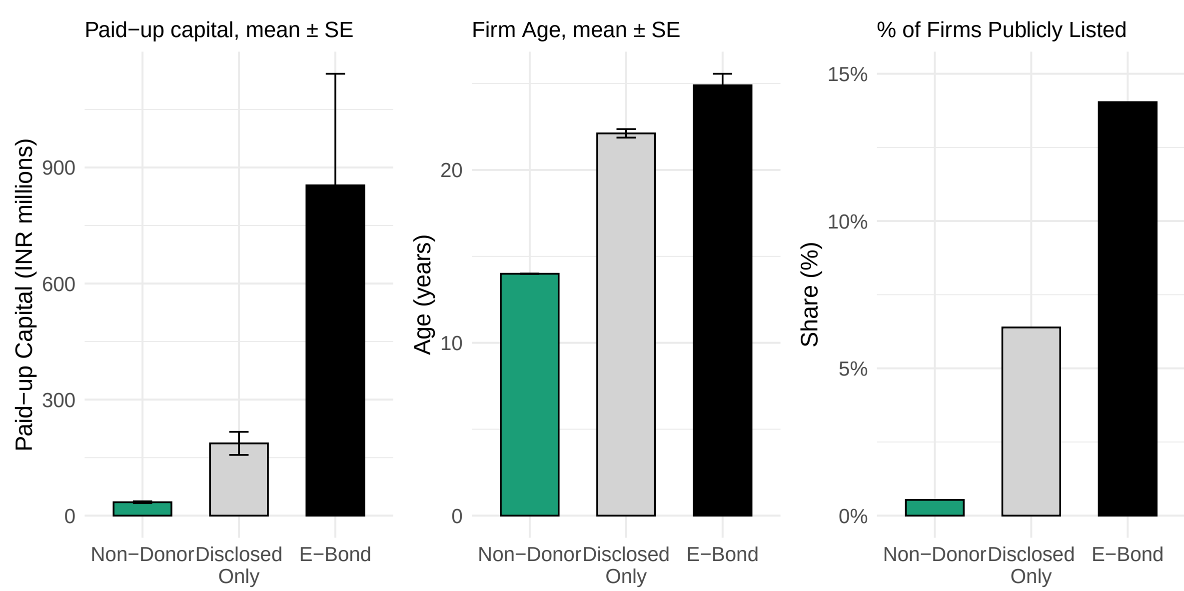
As discussed in Puri (2024), the disclosed donations produce a puzzling pattern for the money in politics literature. In the broader literature on campaign finance, *individual* donors are characterized as *expressive* donors, donating sporadically in small amounts mostly ideologically to a single political party (Bonica 2014; Bouton et al. 2022), while companies tend to be more *strategic*, treating campaign contributions as investments for access and influence (Snyder Jr 1990). In a competitive, federalized, multi-party democracy such as India's, it is surprising that a strategic company, likely exposed to multiple political parties across state, national, and local levels, would donate to a single political party. While disclosed donations depict a puzzling pattern of seemingly non-strategic behavior, the hidden channel appears more classically strategic—companies participate often to donate larger sums to multiple political parties (see figure 5).

FIGURE 2. Political Donations vs. Three-Year Average Net Profit



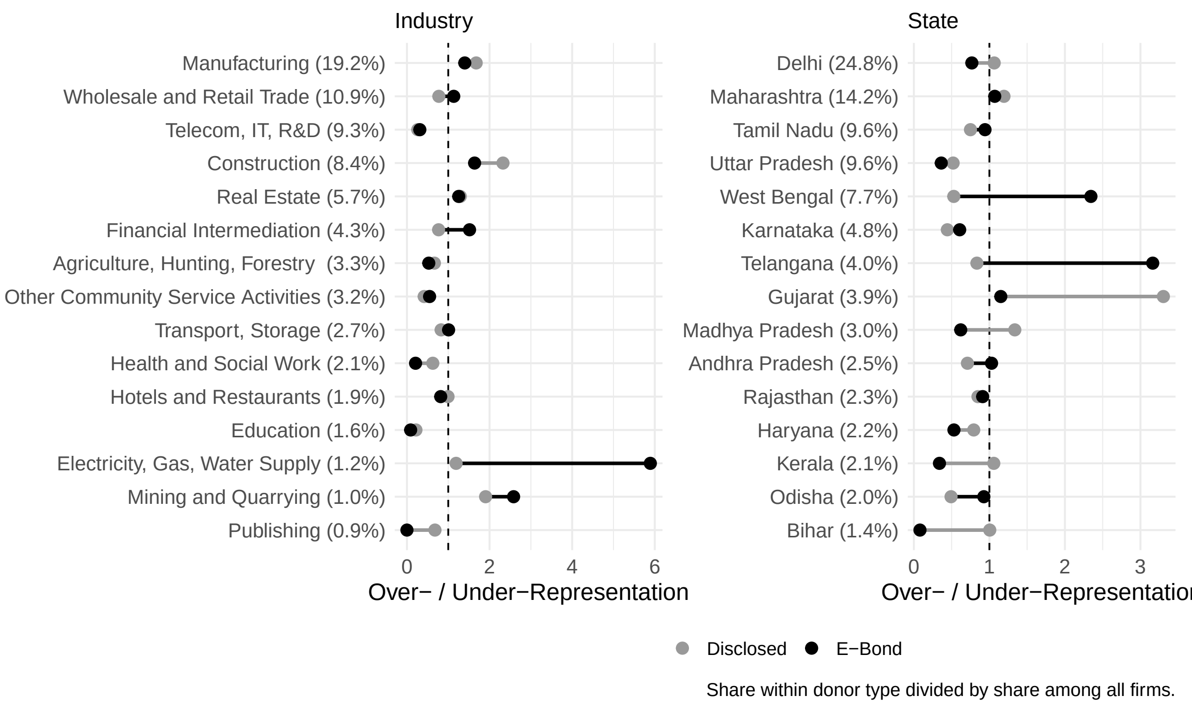
Note: Each dot is a company-fiscal year. Grey dots represent disclosed donations; black dots represent electoral bond purchases. The dashed red line indicates the 7.5% cap on corporate donations as a share of trailing three-year average net profits. The sample is restricted to firms with financial data available in Prowess. Disclosed donations restricted to 2012 onwards (when the 7.5% cap came into effect).

FIGURE 3. Comparing characteristics of electoral bond purchasers with disclosed donors and overall firm population.



Note: The figure displays average size, age, and public listing status across the overall population of firms, disclosed donors and electoral bond buyers.

FIGURE 4. Industry and state representation (top 15 industries and states)



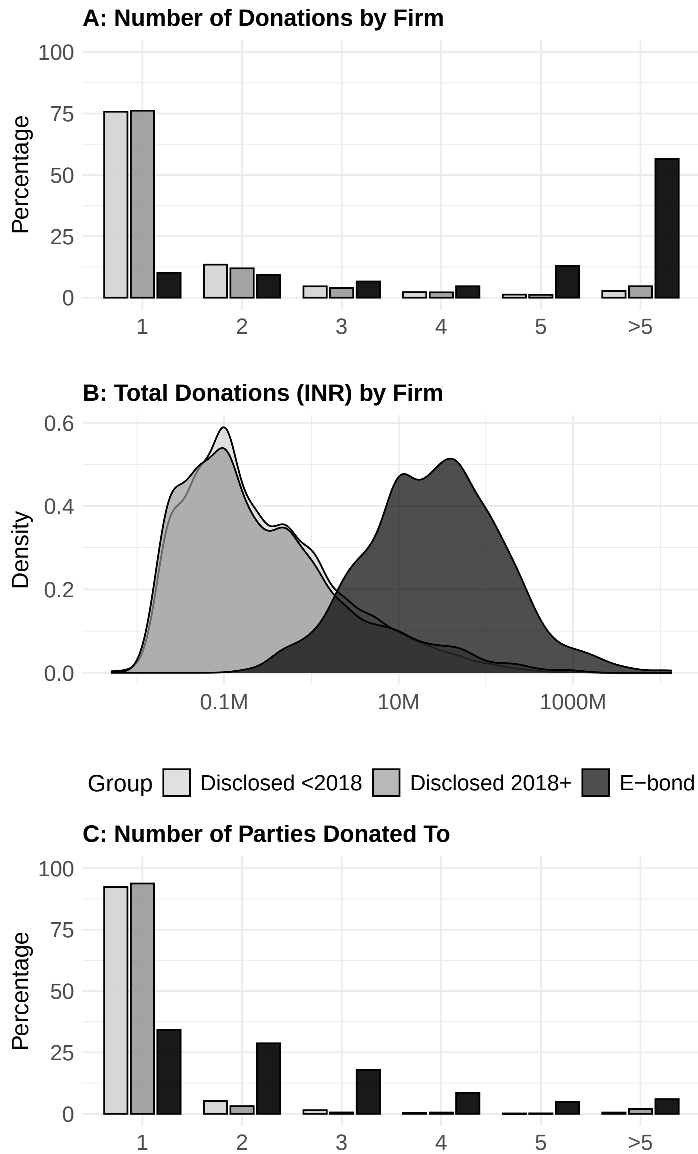
Note: Figure compares industry and state over-/under-representation relative to the formal sector. Percentages in parentheses show share in the firm population. Values >1 imply over-representation, <1 imply under-representation.

Kerr et al. (2014) study the dynamics of firm lobbying in the US and find that while only 10% of publicly listed companies lobby, they exhibit a high degree of persistence (92%) with little entry and exit year-over-year. They argue this indicates high barriers to entry which substantiates theoretical estimates of fixed costs relating to lobbying (Bombardini 2008).

While we too find that only a minority of firms participate in any form of political financing, Figure A3 in the Appendix shows both much lower levels of year-over-year persistence overall, but also a notable persistence gap between the two channels. An electoral bond buyer in year t is 25% likely to purchase a bond again in year $t + 1$, while a disclosed donor is only 10% likely to donate again the following year. This gap is likely explained by similar lobbying fixed costs described by Kerr et al. (2014), that arise from needing to send an envoy to physically purchase and deposit electoral bonds in party accounts on specific dates and in specific bank locations. This more time and effort costly procedure contrasts with the simplicity of the disclosed channel, where companies can hand over checks to party operatives at any time. And so it is reasonable that more sophisticated companies are able to overcome the entry barriers of buying electoral bonds.

What might explain this difference? Drawing on a corporate governance perspective, Puri (2024) highlights how concentrated decision-making agency within family businesses produce this pattern of seemingly non-strategic corporate giving among disclosed donations. The explanation is that family businesses tend to behave like individual donors, giving expressively and often to co-ethnic political parties—a notable feature of individual giving (Grumbach and Sahn 2020; Grumbach et al. 2020; Bouton et al. 2022). While family businesses make up the dominat share of enterprises in India, and indeed among disclosed donors, Puri (2024) finds that family businesses are less likely to take up the electoral bonds channel. This implies that since more strategic firms are participating in the hidden channel, their donations appear more strategic as well.

FIGURE 5. Donation patterns: opaque vs. disclosed



Note: This figure shows how donation firms' donation strategies differ by channel. Panel A shows the distribution of number of donations made by each firm. Panel B shows the distribution of total donated amounts across all firms. Panel C shows the distribution of number of parties each firm donated to. The charts distinguish between disclosed donation behavior pre- and post-the introduction of electoral bonds in 2018. Opaque donors donate more often, in larger amounts, to more parties.

3.4. The private cost of making confidential donations public

For the subset of publicly listed firms, we study in an event study the value effects of the second shock from the regulatory timeline: retroactively revealing the names of all electoral bond buyers between 2019-2024. This was a highly salient news event, with journalists and commentators from global news sources covering this release. How did this affect firm value for companies on the list?

Out of the approximately 900 companies revealed to have bought electoral bonds, 106 were publicly listed entities, and 95 with shares actively traded on the National Stock Exchange (the more liquid exchange compared to the Bombay Stock Exchange).

For our main empirical approach, we follow principles outlined in MacKinlay (1997), and largely track Acemoglu et al. (2016) who study the effect of Tim Geithner's surprise appointment as Treasury Secretary in 2008 on the stock prices of connected companies.

Daily abnormal returns for each firm are calculated as per MacKinlay (1997):

$$AR_{it} = R_{it} - \mathbb{E}\left[R_{it}|X_t\right] \tag{1}$$

Where AR_{it} is the abnormal return for firm i on day t, R_{it} is the actual firm returns on day t, and $\mathbb{E}\left[R_{it}|X_t\right]$ is a benchmark expected return for firm i on day t based on conditioning variables in X_t. Expected returns are calculated using the average market return, or an estimate based on a historical relationship between the daily returns of stock of company i and market returns (CAPM), or key risk factors within the market (Factor model, such as Fama-French). Per Acemoglu et al. (2016), for each company i, we estimate a historical linear relationship between a stock's daily returns and the Nifty 100 over a one year period up to 30 days before the event date. We also calculate excess returns, which simply uses market returns as the benchmark.

Adding up abnormal returns over a given window generates a measure of cumulative abnormal returns, which we use to infer the overall effect of sudden transparency over several trading days.

Equation 2 depicts our main empirical specification.

$$y_{it} = \sum_{s \neq T-1} \beta^s \mathbb{1}[t = s] \times Donor_i + \alpha_i + \eta_t + \gamma t X_i + \epsilon_{it} \tag{2}$$

y_{it} is the abnormal daily return, or excess daily return, for firm i on day t. α_i and η_t are company and date fixed effects. $Donor_i$ takes the value 1 if the company is on the list of donors revealed on T = March 14, 2024. tX_i is a vector of firm-specific controls interacted with time dummies, with coefficients γ. $\hat{\beta}^s$ estimates the average effect of being a donor on abnormal daily returns on day s compared to the reference period. We choose to set March 13 as our reference date—one day before the event.

While α_i captures unobserved time-invariant differences in levels of returns across firms, we also include tX_i which is an interaction of firm-level characteristics with time dummies to ensure the estimates do not capture the effect of the shock on other characteristics that may be correlated with the treatment. Following Acemoglu et al. (2016) we include size, leverage, and profitability as firm-specific covariates. We also include indicators for industry groups and a measure of market capitalization a month before the event date. Appendix G shows how the probability of being a donor varies each of these characteristics. Including these interacted fixed effects implies an assumption of parallel trends conditional on these covariates. We attempt to validate this conditional parallel trends assumption visually by including several pre-periods in the event study window, and by running a placebo analysis where we set the reference period to two weeks before the actual event period. We cluster standard errors at the company level. We cluster standard errors at the stock level.

Multiplying the cumulative abnormal returns with the market capitalization of donor companies immediately prior to the event date estimates the change in corporate value associated with information release, and therefore quantifies the cost to the firm of making confidential donations public.

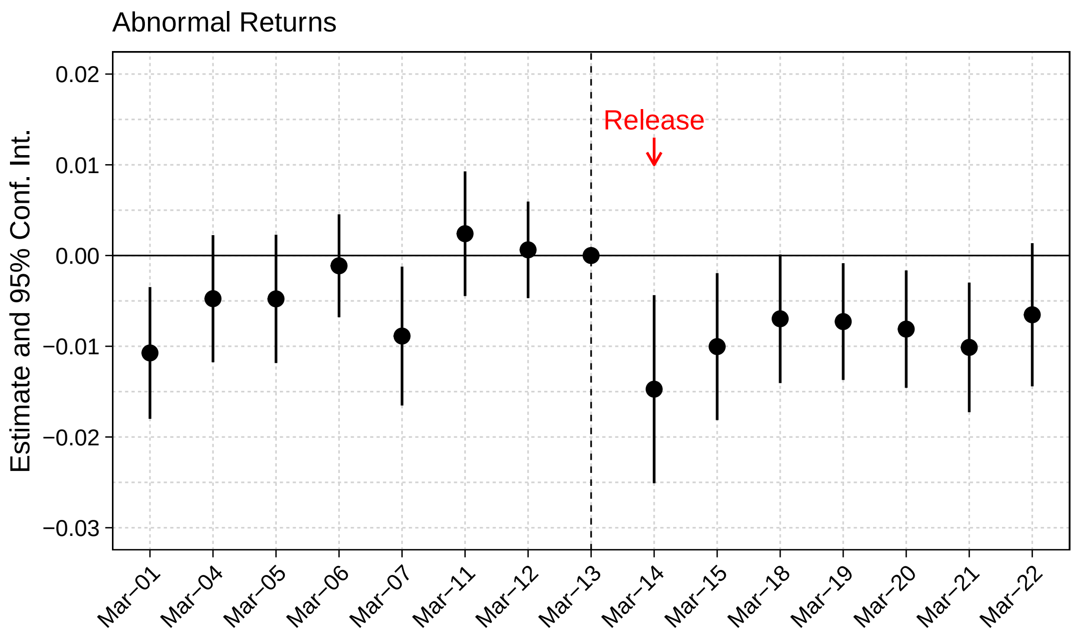
Figure 6 shows the main result of estimating equation 2 on an outcome variable of daily abnormal returns. Companies revealed to be politically active by buying electoral bonds saw a sharp abnormal decline on the day of the release (on average, a 1.5% abnormal decline), persisting for several trading days after. Appendix I.1 reports the results across a range of different empirical specifications, including winsorizing or trimming daily returns to ensure the results are not driven by outliers. The negative effect is consistent in all specifications, with qualitatively similar magnitudes and significance.

The pre-period shows no visually apparent trend, with most estimates in the pre-period generally not significantly separable from zero. Additionally, we run a placebo test where we replace the reference period (March 13, 2024) with one from two-weeks before the event date (February 26, 2024). As shown in appendix I.3, neither the pre-period nor the post-period show a significant and systematic difference between the two groups. These diagnostic tests suggest a strong treatment effect of the information shock, revealed on the event date.

An important detail is that the list of donors was revealed *after* market-hours on the 14th, even though abnormal daily price action is evident on the day itself. The pre-announcement decline reveals the negative effect was driven by not just the release of information, but also the *anticipation* of its release.

Even though the Supreme Court had required the list be revealed by March 6 in its original February 15 ruling, commentators remained skeptical that the State Bank of India would actually adhere to this timeline (Vaishnav 2024b). This skepticism was partially vindicated when the SBI requested an extension until June 30. But the Court rejected their request, but revised the release date to be March 15. The threat of information became credible on March 12, when

FIGURE 6. Event Study: Daily Abnormal Returns



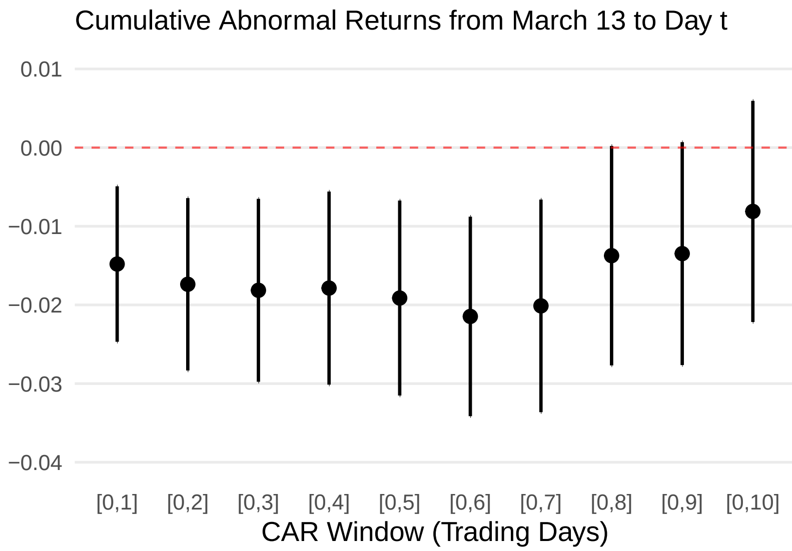
Note: OLS estimation of equation 2. Outcome variable: abnormal returns, defined as the difference between a stock's actual daily returns and predicted returns based on the market's daily return and one year's relationship between the stock and market returns. Error bars represent 95% confidence interval. Size, leverage, return on equity, market capitalization (as of Feb 15, 2024) and industry sections all interacted with time dummies. Names of donors released on March 14.

the SBI submitted a password-protected USB drive containing the list of donors to the Election Commission. At this point, it was clear that the ECI was going to reveal the information over the next few days, and some stocks started pricing in what was expected to be in the information release.

This market pattern is consistent with empirical studies of *pre*-announcement and *post*-announcement drift around salient market or corporate news events, like FOMC meetings (Lucca and Moench 2015), company earnings, or index inclusions or exclusions (Fernandes and Mergulhão 2016). These studies find equity markets to move in advance of information releases, despite low trading volumes, followed by a bump in trading volumes *after* the information is actually revealed (see appendix I.4)—indicating more of a retail reaction to news (Frazzini and Lamont 2007)—as well as a post-announcement drift, where prices do not correct immediately in one go, but take several days to percolate through.

Some research has tied this pre-announcement drift to private information leaks, for instance between the Fed and market participants (Cieslak et al. 2019). But pre-announcement price action does not necessarily require leaked information and could emerge from the rational

FIGURE 7. Cumulative Abnormal Returns After Revelation



Note: This figure presents the coefficients on being a treated firm (i.e. on the list of previously-hidden donors) on various windows of cumulative abnormal returns (CAR) starting from the event date (March 14) to 10 days following.

behavior from market participants facing uncertainty (Cocoma 2018). More concretely in the case of electoral bonds in India, it was perhaps not a big surprise which companies were likely to be on the list of donors in the first place, with about half of the companies eventually revealed as donors previously giving through disclosed channels in any case.[14]

We formally test the cumulative effect of this information release on the cumulative abnormal returns for companies revealed to be on the list versus those companies not on the list of political donors. Table 1 reports the conditional average treatment effect on the treated (CATT) on cumulative abnormal or excess returns across various windows of trading days after the event date. We find treated firms experience a sharp and significant underperformance on the event day (March 14) and over the following week relative to normal expectations and the overall market. More precisely, over seven trading days after the information release, treated firms experience, on average, a 2pp cumulative abnormal underperformance versus non-treated firms. This significant negative effect only lasts up to 7 trading days, after which the difference between treated and non-treated firms starts to reduce.

As a robustness exercise, we implement an alternate procedure, synthetic control method, that compensates for potential violations in parallel trends. A difference-in-difference approach assumes parallel trends between treatment and control groups hold after including covariates and firm-fixed effects to capture unobservable characteristics. The synthetic control method

[14] For instance, the financial presses reported Adani enterprise stocks experiencing a sharp selloff in anticipation of the release of the electoral bond buyers, with the conglomerate reported to have close ties to the government (Iyengar 2024).

TABLE 1. Conditional ATT on Cumulative Returns

	Cumulative Abnormal Return			Cumulative Excess Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Post x Donor	−0.015**	−0.020**	−0.008	−0.014*	−0.018*	−0.005
	(0.005)	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)
CAR Window	[0,1]	[0,7]	[0,10]	[0,1]	[0,7]	[0,10]
Num Stocks	1458	1458	1458	1458	1458	1458
FE: ISIN	✓	✓	✓	✓	✓	✓
FE: Trading Day	✓	✓	✓	✓	✓	✓
R2	0.658	0.653	0.567	0.616	0.644	0.564

Note: OLS estimation with period dummies interacted with total assets, leverage, return on equity, market capitalization as of Feb 15, and NIC product section for each firm. Firm financial data as of September 30, 2023. Firm-clustered standard errors reported in parentheses.

compensates for potential violations of parallel trends by reweighting units to match pre-treatment trends (Arkhangelsky et al. 2021). Developed by Abadie and Gardeazabal (2003); Abadie et al. (2010, 2015), this process involves constructing a synthetic version of each treated unit based on all control unit outcomes, weighted by its fit in the pre-treatment period, and is sometimes used as a robustness test for difference-in-difference procedures.[15] We follow Acemoglu et al. (2016), given its similar setting of multiple treated units, and aggregate treated firms' actual returns deviations from their synthetic counterfactuals. We estimate confidence intervals using permutation tests as recommended by Abadie et al. (2010); Abadie (2021). We provide detailed descriptions of the process in appendix K.

Estimating the cost of revealing political connections. As of March 13, 2024, donors constituted approximately 5% of all publicly listed and actively traded companies on the NSE, but accounted for close to 14% of the overall market capitalization of over $4 trillion, i.e. $609 billion.

A 2% abnormal decline over 7 days on a market capitalization of $609 billion implies a value destruction in the order of $12 billion that can be traced to the sudden revelation of companies' political participation. For context, the entire electoral bonds scheme raised a total of $1.7 billion (Traveli and Kumar 2024), making the short-term cost of revealing political connections more than 6 times the actual benefits transferred to the political parties, and over 100 times what these specific companies donated.

Over the long-run however, the effect is more muted, with cumulative abnormal or excess returns of treated and non-treated firms indistinguishable after 10 days.

[15] See for instance Acemoglu et al. (2016); Mirenda et al. (2022)

We replicate these findings in direction, magnitude, and duration of effect using a synthetic control approach (appendix K).

Taken together, these facts indicate that the introduction of an opaque channel did not merely shift existing donation activity underground, but attracted a distinct set of firms pursuing qualitatively different political strategies, for whom confidentiality carried substantial private value.

4. Hiding from Retribution

Why would a firm seek to hide its political activities? The answer is not obvious *ex ante*. The weight of evidence in the money-in-politics literature suggests firms *benefit* from political connections (Faccio 2006; Fisman 2001), implying they might stand to gain from publicizing them. Yet a burgeoning literature documents that political connections are a double-edged sword. Firms may face retaliation when a rival party assumes power (Siegel 2007), suffer reputational costs that erode consumer demand or investor confidence (Borisov et al. 2016; Bhandari 2022), or see their operations distorted by political pressure (Bertrand et al. 2018; Akcigit et al. 2023).

We propose a distinct mechanism rooted in contexts where governments wield discretionary power to punish political opponents. In such environments, firms may wish to donate for strategic purposes—to curry favor, hedge political risk, or secure access—but are restrained by the fear of retribution from rival parties. A confidential channel allows firms to execute their political strategy while reducing downside risk.

4.1. The threat of state retribution in India

Protecting donors from political retribution was the stated rationale for the electoral bonds scheme. When introducing the Finance Bill of 2017, Finance Minister Arun Jaitley said, "People donating to a political party usually don't like to disclose their identity as they fear repercussions from rival political parties. By purchasing electoral bonds, they can keep their identity secret" (Hindustan Times 2017).

Paradoxically, however, the party that controlled the most powerful tools for retribution during the electoral bonds period was the BJP itself, which came to power nationally in 2014 and has remained the dominant party at the central level throughout. The BJP controls central investigative agencies including the Income Tax Department, the Central Bureau of Investigation (CBI), and the Enforcement Directorate (ED). These agencies have broad mandates: the ED investigates money laundering offenses under the Prevention of Money Laundering Act (PMLA), while the CBI handles a wider range of criminal investigations, including corruption and fraud.[16]

[16] The Enforcement Directorate was established in 1956 and derives its authority primarily from the Foreign Exchange Management Act (FEMA) and the Prevention of Money Laundering Act (PMLA). The CBI, established in 1963, investigates cases referred by state or central governments or courts.

Since 2014, the ED has seen a marked uptick in its activity, with observers noting its increasing use against opposition politicians, journalists, NGOs, and corporations (Vaishnav 2024a).[17] Figure A12 in the Appendix shows the high baseline level and rising rate of central government agency raids since the BJP came to power nationally in 2014.

Raids by these agencies mire individuals and companies in protracted legal proceedings that can have negative repercussions for the fundamental health of the firm—through management distraction, frozen assets, and disrupted operations—and may also cause significant reputational damage (Colonnelli and Prem 2022; Cohen and Li 2025).

We therefore hypothesize that firms sought out the covert channel of electoral bonds as a way to strategically allocate political donations while reducing the downside risk of retribution. We provide evidence for this hypothesis in three ways: (1) under opacity, firms donate more broadly across parties, especially around closely contested elections; (2) firms most exposed to external scrutiny—particularly publicly listed companies—disproportionately substitute into the hidden channel; and (3) at the moment of revelation, the market reaction is concentrated among firms most exposed to political retribution risk.

4.2. Hedging across parties under opacity

In a competitive, multi-party federal democracy, politically active firms are incentivized to hedge their bets by donating across multiple political parties. But such a strategy risks political retribution in the event a rival party comes to power and punishes opponent supporters. Opacity, therefore, reduces the retribution risk firms face when deciding to donate to multiple parties.

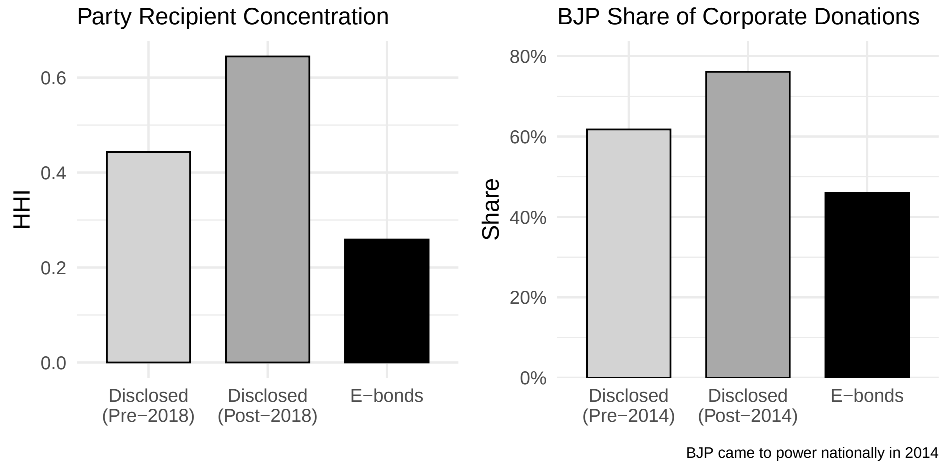
We present two pieces of evidence that firms use the anonymous channel to hedge against political risk. First, in aggregate, despite the BJP's single-party dominance at the national level during the entire period of electoral bonds (2018–2024), the BJP received a smaller share of total anonymous donations than of disclosed donations. This pattern extends to the concentration of political party recipients more broadly. Figure 8 shows that electoral bonds were spread more evenly across parties than disclosed donations, consistent with firms using opacity to diversify their political portfolio.

Second, we use state-level elections as sharp instances when companies face heightened incentives to hedge ahead of potential political change. Using approximately 100 state-level elections during the period, we examine the donation behavior of firms headquartered in poll-bound states in the six months prior to each election. We compare the likelihood that companies donate to multiple political parties during this election window across close and non-close elections. We define close elections as those where the mean margin of victory across single-member districts in the state falls below the overall median (see appendix H).

Figure 9 presents the results. Compared to disclosed donors, anonymous donors are more likely to make multi-party donations during election periods in general, and *especially* around

[17] Commentators have characterized this pattern as "weaponizing" these arms of the state (The Wire 2022).

FIGURE 8. Party Recipient Differences: Disclosed vs. Anonymous Channels



Note: This figure shows how opacity changed firms' willingness to hedge donations across multiple political parties. The left panel shows the concentration of donation recipient parties across disclosed and opaque channels—electoral bonds were spread more evenly across parties. The right panel focuses specifically on the BJP, which has dominated national politics since coming to power in 2014, and yet received less as a share of donations under opacity than through disclosed channels.

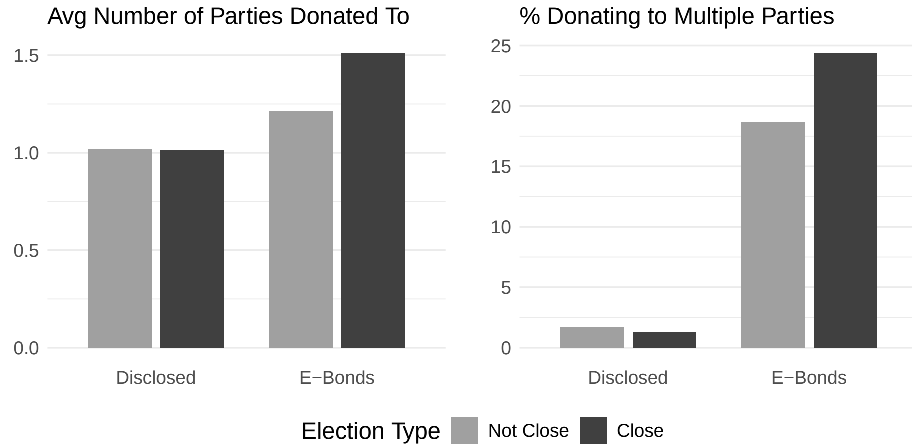
close elections where political uncertainty—and therefore the potential for retribution by an incoming rival party—is greatest. Disclosed donor hedging behavior, by contrast, appears less sensitive to election closeness, consistent with the interpretation that firms are reluctant to hedge openly when the political stakes are high.

4.3. Strategic firms substitute into the hidden channel

Given the strategic value of anonymity documented above—the ability to hedge across parties and manage retribution risk—publicly listed companies represent a most-likely case for taking up the hidden channel. Listed firms face greater external monitoring from investors, analysts, regulators, and the media, and have stronger incentives for economic optimization of their political strategy. Their political activities are more visible and therefore more exposed to retributive action by rival parties. If opacity is valuable for managing political risk, publicly listed firms should be the first to substitute into the anonymous channel when it becomes available.

We test this prediction using a difference-in-differences event study design. We construct a balanced panel of all "ever-donor" firms—companies that made at least one donation via either channel—for every year from 2013 to 2023. We flag corporations publicly listed before 2018 as treated and non-publicly held corporations as controls. We aggregate annual donations via electoral bonds and disclosed channels at the firm-year level. We estimate how the donation strategy of publicly listed firms evolves in response to the introduction of electoral bonds in

FIGURE 9. Multi-Party Hedging Around Close Elections



Note: This figure compares multi-party donation behavior around state elections across disclosed and anonymous channels, split by election closeness. Close elections are defined as those where the average margin of victory across constituencies falls below the sample median. The figure shows that anonymous donors are more responsive to political uncertainty than disclosed donors.

2018:

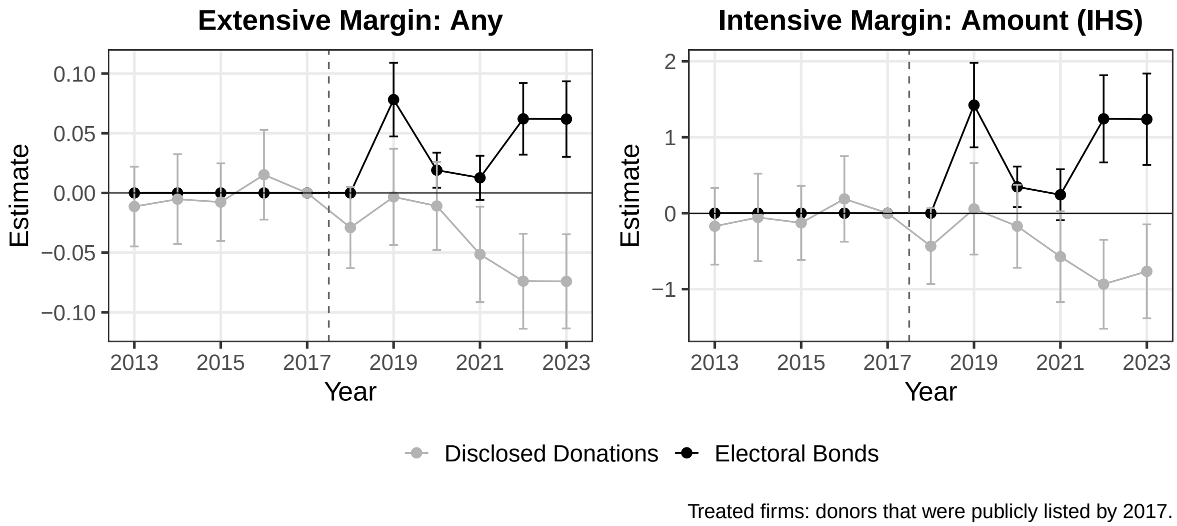
$$y_{it} = \alpha_i + \gamma_t + \sum_{s \neq 2017} \beta_s D_i \cdot \mathbf{1}[t = s] + \epsilon_{it} \tag{3}$$

where y_{it} is the outcome variable for firm i in year t, and D_i takes the value 1 if firm i was publicly listed by 2017.

Figure 10 presents the results on both the extensive margin (any donation) and the intensive margin (amount donated, in inverse hyperbolic sine). After the introduction of electoral bonds, publicly listed firms are clearly more likely to take up the new anonymous channel and symmetrically reduce their participation in disclosed channels. Table 2 reports the static difference-in-differences estimates and confirms a strong and significant positive effect on electoral bond participation (3.9 percentage points, $p < 0.01$) and a corresponding negative effect on disclosed donations of comparable magnitude. The bond share of total donations increases by 16 percentage points. These results suggest that for publicly listed firms, the hidden channel is a *substitute* for—rather than a complement to—disclosed giving.

Alternative explanation: hiding from stakeholders.. An alternative interpretation is that firms seek opacity not to avoid political retribution, but to shield themselves from customers or other stakeholders who have a distaste for corporate political activity (see e.g. Conway and Boxell (2024)). If stakeholder backlash were a primary driver, we would expect downstream, consumer-facing firms to disproportionately substitute into the anonymous channel. We test

FIGURE 10. Publicly Listed Firms Substitute from Disclosed to Hidden Channel



Note: This figure presents estimates from the event study specification in equation 3. Each panel overlays coefficients for electoral bonds (black) and disclosed donations (grey). The left panel shows the extensive margin (any donation); the right panel shows the intensive margin (amount donated, IHS-transformed). The sample is restricted to "ever-donors." Treatment ($D_i = 1$) if a firm was publicly listed by 2017.

for this by following Kisat and Phan (2020) and use a measure of industry upstreamness from Antràs et al. (2012); Antràs and Chor (2018)—firms in industries closer to final consumption (lower upstreamness) are more exposed to consumer sentiment.[18]

Table 3 presents the difference-in-differences estimates comparing downstream (below-median upstreamness) to upstream firms. We find no significant substitution effect on any outcome—neither the probability of purchasing electoral bonds, nor the amount donated, nor the bond share of total donations. Consumer-facing firms did not differentially substitute into the hidden channel. This null result provides little support for a stakeholder-driven explanation of opacity demand, and is consistent with the retribution channel being the primary motive.

It is worth noting how these results about the behavior of publicly listed firms bear on the broader money-in-politics literature. Due to data limitations, most studies on corporate campaign finance are restricted to publicly listed companies. Benefiting from access to all firms in the formal sector in India, we show that publicly listed firms behave systematically differently from non-listed entities, actively seeking to obscure the extent of their political giving.

4.4. Who suffers when political activities are revealed?

If firms use anonymous donations to manage political retribution risk, then the costs of losing anonymity should be concentrated among firms with the greatest exposure to such risk. We

[18]We provide details of the procedure to compute upstreamness in appendix F.

TABLE 2. Electoral Bond Takeup: Public vs Non-Public Firms

	P(Buy Bonds) (1)	P(Disclosed) (2)	Bonds (IHS) (3)	Disclosed (IHS) (4)	Bond Share (5)
Public × Post-2017	0.039***	−0.039***	0.749***	−0.437***	0.160**
	(0.007)	(0.010)	(0.132)	(0.150)	(0.072)
Num Obs	69927	69927	69927	69927	6581
FE: Firm	✓	✓	✓	✓	✓
FE: Year	✓	✓	✓	✓	✓

Note: OLS estimation with two-way fixed effects. Treatment: companies listed by 2017 vs never public. Post period: 2018-2023. IHS = inverse hyperbolic sine (asinh) transformation. Bond share computed among donors only. Firm-clustered standard errors reported in parentheses.

TABLE 3. Electoral Bond Takeup: Downstream vs Upstream Firms

	P(Buy Bonds) (1)	P(Disclosed) (2)	Bonds (IHS) (3)	Disclosed (IHS) (4)	Bond Share (5)
Downstream × Post-2017	−0.001	0.006	−0.015	0.074	−0.034
	(0.002)	(0.005)	(0.044)	(0.068)	(0.049)
Num Obs	51689	51689	51689	51689	4917
FE: Firm	✓	✓	✓	✓	✓
FE: Year	✓	✓	✓	✓	✓

Note: OLS estimation with two-way fixed effects. Treatment: downstream firms (below median upstreamness) vs upstream firms (above median). Post period: 2018-2023. IHS = inverse hyperbolic sine (asinh) transformation. Bond share computed among donors only. Firm-clustered standard errors reported in parentheses.

exploit the heterogeneity in the market reaction to the March 14 revelation to test this prediction. As documented in Section 3.4, the average publicly listed donor firm experienced a cumulative abnormal return of approximately −2% over the seven trading days following the disclosure. We now examine which firms drive this effect.

We split the 95 publicly listed donor firms into treatment arms along three dimensions that map onto the retribution mechanism: known political affiliation, enforcement history, and geographic exposure to political parties. We estimate:

$$CAR_{it} = \alpha_i + \delta_t + \gamma t X_i + \beta_G Donor_{it}^G + \epsilon_{it} \tag{4}$$

where the outcome variable is 7-day cumulative abnormal returns, and we vary the treatment group G across treatment arms while keeping the control group of non-donors constant. Standard errors are clustered at the firm level.

TABLE 4. Cumulative Abnormal Returns: Heterogeneity Analysis

		Known Party Affiliation		Enforcement History		HQ State	
	All Donors	Not Just BJP	BJP-Only	Recently Raided	Not Recently Raided	BJP-State HQ	Non-BJP-State HQ
7-day CAR	−2.012***	−3.699**	−1.954*	−0.782	−2.331***	−1.340	−2.947***
	(0.689)	(1.565)	(1.108)	(0.988)	(0.809)	(0.902)	(0.952)
N	95	11	32	19	76	56	39

Note: DiD coefficient × 100 (percentage points). Each column compares the indicated donor group against matched non-donor firms. "Not Just BJP" donors also donated to at least one non-BJP party. Recently raided firms faced enforcement action by ED/IT/CBI in the two years before the February 2018 bond scheme launch. Firm clustered standard errors. HQ state classification reflects governing party as of March 2024. * p<0.10, ** p<0.05, *** p<0.01.

TABLE 5. Daily Returns on March 22, 2024 by Donor Party Affiliation

	Daily Abnormal Returns			Daily Excess Returns		
	BJP-Only	Multi-Party	Non-BJP	BJP-Only	Multi-Party	Non-BJP
March 22	0.951**	0.511*	0.515	1.066**	0.643**	0.569
	(0.431)	(0.252)	(0.420)	(0.437)	(0.269)	(0.430)
Num Obs	35	35	25	35	35	25

Note: Daily abnormal return = stock return − predicted return (market model). Daily excess return = stock return − NIFTY100 return. Party classification from full e-bonds data (not limited to disclosed donors). Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Known party affiliation.. On March 14, investors could not observe which parties each donor had given to—the party-level linkage was only released on March 21. However, for some donors, political affiliation could be inferred from prior disclosed donations. We classify donors as "Not Just BJP" if their disclosed giving history revealed donations to at least one non-BJP party, and "BJP-Only" otherwise.

If the retribution mechanism is operative, firms perceived as supporting opposition parties should face a sharper market penalty, since their political activities carry greater risk of antagonizing the party in power. Table 4 confirms this: donors with known non-BJP affiliations experienced a 7-day CAR of −3.7% ($p < 0.05$), nearly double the overall effect and roughly twice the magnitude for BJP-only donors (−1.95%, $p < 0.10$).

Further evidence emerges from the March 21 release, when the ECI published party-level linkages allowing investors to see exactly which parties each firm donated to. Table 5 shows that on the first trading day after this second release (March 22), BJP-only donors experienced a significant *positive* abnormal return—consistent with a partial reversal as the market learned these firms' donations were less politically risky than initially feared.

Enforcement history and a spotlight effect.. We next examine whether a firm's prior exposure to government enforcement actions moderates the market reaction. Firms that had recently been the target of raids by the ED, CBI, or Income Tax Department in the two years prior to the event were already under the scanner—new information of their political entanglements, therefore, would be arguably less surprising to the market. For these firms, learning about electoral bond purchases adds less incremental information about their political exposure.

By contrast, firms with no recent enforcement history—and therefore a cleaner public image—face a *spotlight effect*: the sudden revelation of their political activities puts them under scrutiny for the first time. Even though the electoral bonds scheme was entirely legal, the disclosure was a high-salience news event that carried strong associations with scandal. Figure A11 in the Appendix shows how media coverage spiked sharply after the event, and the language of that coverage was overwhelmingly negative—terms like `extort`, `corrupt`, `scam`, and `bribe` were far more prevalent in electoral bond reporting than in general election news.[19]

Consistent with the spotlight effect, Table 4 shows that firms *not* recently raided experienced a significant 7-day CAR of -2.3% ($p < 0.01$), while recently raided firms show a statistically insignificant effect (-0.8%). The revelation puts newly exposed firms in the spotlight, whereas firms already known to be embroiled in enforcement activity see less incremental reputational damage.

Geographic exposure to retribution.. Finally, we examine whether the market reaction varies by the political environment of the firm's headquarters. Firms headquartered in states governed by non-BJP parties face a different retribution calculus: their state-level exposure to opposition parties may make their electoral bond participation appear more strategically motivated—and therefore riskier upon revelation. Table 4 shows that firms headquartered in non-BJP-governed states experienced a significant 7-day CAR of -2.9% ($p < 0.01$), while firms in BJP-governed states show an insignificant effect (-1.3%). This is consistent with investors perceiving greater political risk for firms operating in environments with active partisan competition.[20]

Taken together, these results paint a consistent picture. Firms sought out anonymous channels primarily to manage the risk of political retribution. Under opacity, they hedged more broadly across parties—especially when elections were closely contested. The firms most exposed to external scrutiny substituted most aggressively into the hidden channel. And when anonymity was stripped away, the market penalty fell hardest on firms with opposition-party ties, those newly thrust into the spotlight, and those in politically competitive environments.

[19] We measure this using term frequency–inverse document frequency (TF-IDF) ratios computed over a corpus of electoral bond news versus a reference corpus of Indian election news from `newsapi.org`. See appendix L for details.

[20] An alternative interpretation is that firms in non-BJP states were more likely to have donated to non-BJP parties, making the geographic heterogeneity partially collinear with the party affiliation result.

There is an irony to these findings. The BJP government introduced electoral bonds arguing that donor anonymity was needed to protect firms from retribution. Yet as the dominant party controlling the central government's investigative apparatus, the BJP was itself the primary source of retribution risk. By creating a confidential channel, the government may have paradoxically empowered the opposition: firms that might otherwise have refrained from supporting rival parties—out of fear of the ruling party's retaliatory capacity—were freed to do so under the cover of anonymity.

5. Conclusion

This paper exploits India's electoral bonds scheme to provide the first comprehensive account of corporate dark money. Anonymous donations dwarfed disclosed contributions two-to-one and attracted fundamentally different participants: larger, publicly-listed firms that donated strategically to multiple parties rather than sporadically to single parties. The data reveal that when firms can hide, they behave like the strategic political actors theory predicts—not the expressive donors that disclosed data suggest.

The market's reaction to sudden transparency was swift and severe. Donor firms lost $9 billion in market value—five times the total funds raised through electoral bonds. This punishment stemmed from media-driven reputational damage, not fundamental reassessment, evidenced by losses concentrated among high-coverage firms and rapid recovery within ten days. The magnitude of these losses explains why firms pay substantial costs to keep political activities hidden.

These results carry important implications for both scholarship and policy. For scholars studying corporate political activity, our findings highlight that visible "hard money" contributions likely represent only a fraction of total corporate political engagement and may systematically differ from hidden channels in ways that bias our understanding of firm political strategies. The fact that more sophisticated firms preferentially select into hidden channels suggests that studies focusing solely on disclosed contributions may underestimate the extent and strategic nature of corporate political influence. For policymakers, our evidence demonstrates that transparency requirements impose real costs on political actors—costs that may be necessary to maintain democratic accountability but that also create powerful incentives for circumvention. The Indian case shows how even well-intentioned attempts to create anonymous giving channels can undermine transparency without eliminating the underlying reputational and political risks that drive firms to seek opacity in the first place.

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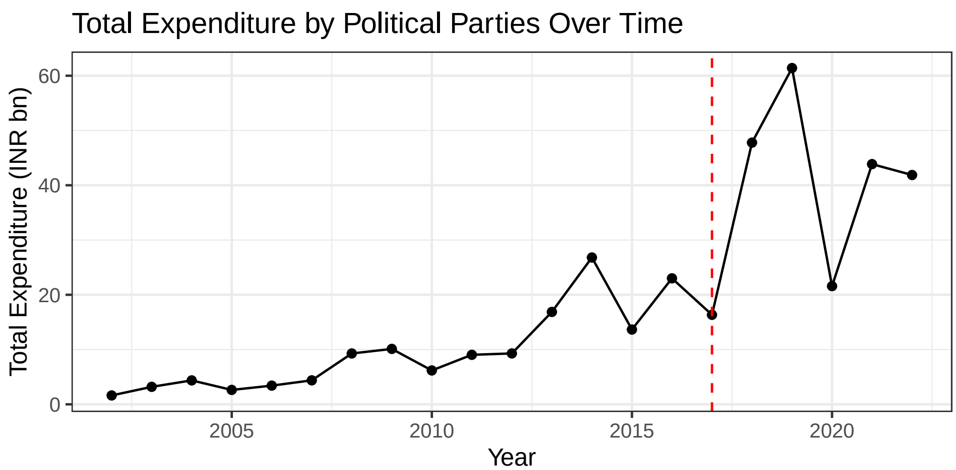
Appendix A. Appendix

Appendix B. Party Expenditure

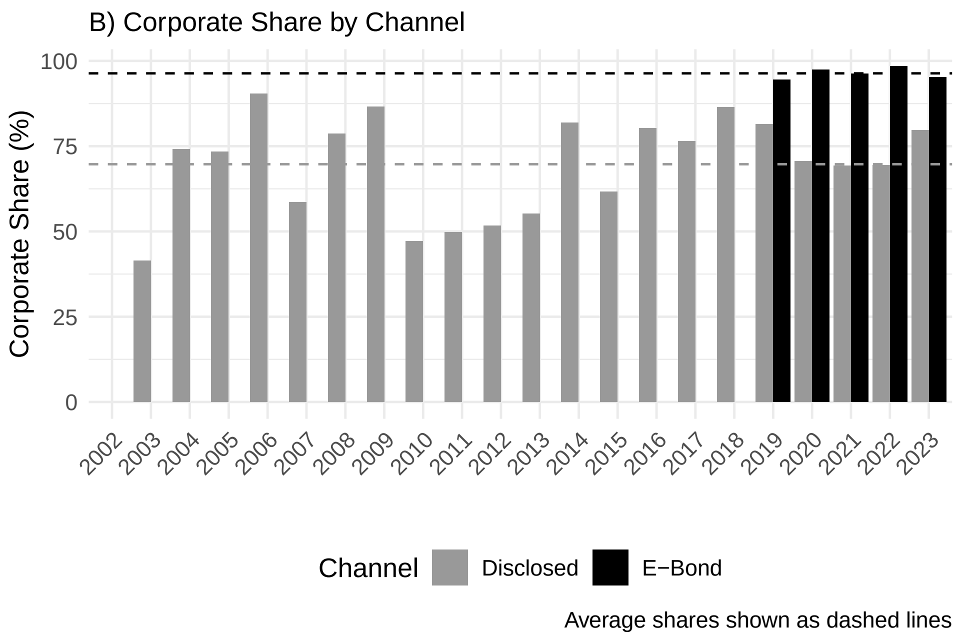
FIGURE A1. Party Expenditure Over Time



Note: The figure shows political parties' reported annual expenses, with the red dashed line indicating the introduction of electoral bonds. Aggregate party expenditures tends to spike in national election years (2004, 2009, 2014, 2019), but 2018 shows a sharp rise in party expenses despite being an off-election-cycle year.

Appendix C. Corporate Participation

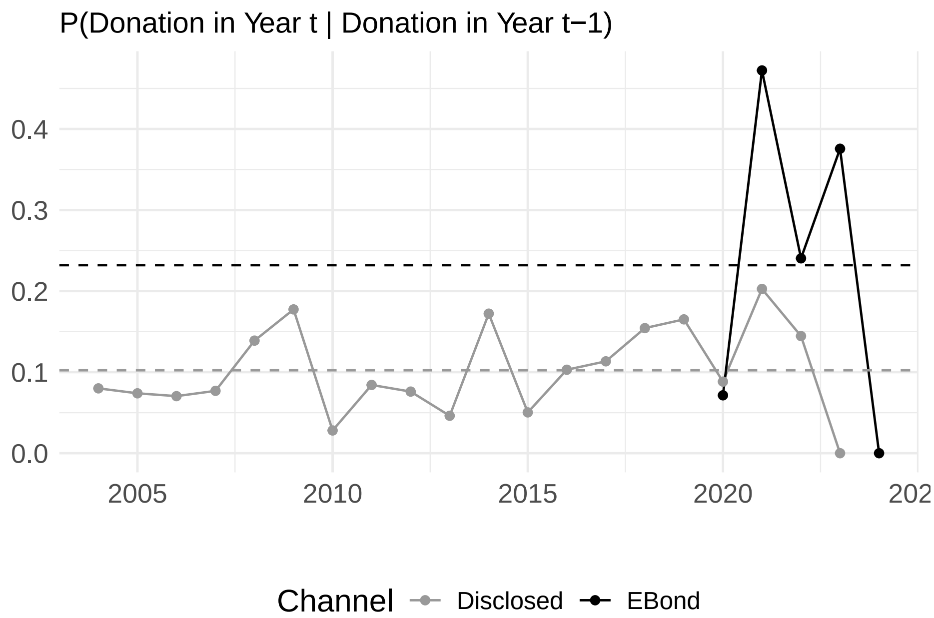
FIGURE A2. Corporate Participation in Disclosed vs Hidden Campaign Finance Channel



Note: This figure presents the corporate donations as a share of the annual amounts raised each year. Corporate donors defined using a set of corporate key words (like "pvt ltd" or "enterprise"). Each year corresponds to the start of the fiscal year, i.e. "2019" refers to the period April 1, 2019 – March 31, 2020. Overall, while corporate giving dominates overall campaign finance, corporate giving almost fully captures donations via hidden electoral bonds.

Appendix D. Donation Persistence

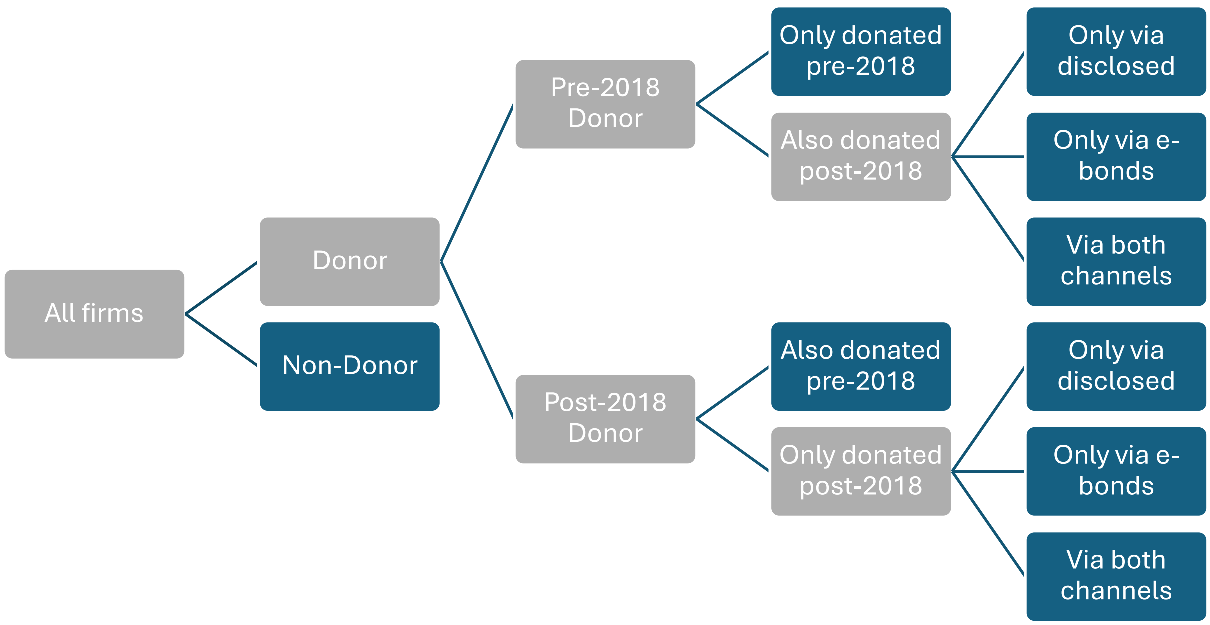
FIGURE A3. Donation Persistence Gap By Channel



Note: This figure shows year-over-year persistence in donation by firm, i.e. what proportion of firms that donated in year $t-1$ also donated in year t. Dashed lines indicate averages by channel. Unlike in Kerr et al. (2014), the persistence of lobbying is lower overall, but electoral bond participants are stickier.

Appendix E. Firm Characteristics by Donation Channel

FIGURE A4. Donation Flowchart



Note: Flowchart of donation decision. Cells in blue indicate categories of companies with detailed characteristics presented in tables below.

Here we provide detailed characteristics of donors by each donation channel category.

We split the characteristics into two tables: firms that donated pre-2018, i.e. before the introduction of the electoral bonds channel. And firms that donated after the introduction of the channel. See figure A4 for a visual depiction of the donation choice.

Firm Characteristics by Donor Type

		Pre-2017 Donors			
	Non-Donor	Only Pre	Pre+Post Disclosed Only	Pre+Post Bond Only	Pre+Post Both
No. Firms	1,183,733	2,656	437	38	62
Avg Age (yrs)	14	26	28	33	40
Avg Paid-up Capital (INR, m)	34	813	473	626	1,330
Share Public	0.005	0.085	0.165	0.395	0.371
Industry Share	NA	NA	NA	NA	NA
Manufacturing	0.192	0.307	0.339	0.368	0.419
IT	0.093	0.023	0.023	0.026	0.016
Construction	0.083	0.191	0.247	0.105	0.113
Real Estate	0.057	0.082	0.059	0.053	0.081
Finance	0.043	0.045	0.034	0.158	0.032
Utilities	0.011	0.014	0.007	0.079	NA
Mining	0.009	0.020	0.018	NA	0.016
State Share	NA	NA	NA	NA	NA
Andhra Pradesh	0.025	0.017	0.025	NA	0.027
Delhi	0.248	0.238	0.213	0.267	0.135
Gujarat	0.039	0.148	0.190	0.067	0.081
Haryana	0.022	0.010	0.009	0.022	0.027
Karnataka	0.048	0.025	0.027	NA	0.014
Maharashtra	0.142	0.235	0.174	0.289	0.257
Punjab	0.010	0.012	0.031	NA	0.014
Tamil Nadu	0.096	0.054	0.076	NA	0.054
Telangana	0.040	0.035	0.031	0.067	0.095
Uttar Pradesh	0.096	0.027	0.036	0.044	0.081
West Bengal	0.077	0.051	0.034	0.178	0.081

Firm Characteristics by Donor Type

		Post-2017 Donors			
	Non-Donor	Post+Pre Also	Post-Disclosed Only	EBond Only	Post-Both
No. Firms	1,183,733	537	3,021	563	66
Avg Age (yrs)	14	30	22	23	26
Avg Paid-up Capital (INR, m)	34	583	187	791	942
Share Public	0.005	0.205	0.064	0.107	0.212
Industry Share	NA	NA	NA	NA	NA
Manufacturing	0.192	0.350	0.336	0.249	0.303
IT	0.093	0.022	0.025	0.028	0.045
Construction	0.083	0.222	0.199	0.144	0.106
Real Estate	0.057	0.061	0.066	0.073	0.045
Finance	0.043	0.043	0.023	0.067	0.076
Utilities	0.011	0.011	0.014	0.082	0.015
Mining	0.009	0.017	0.016	0.020	0.076
State Share	NA	NA	NA	NA	NA
Andhra Pradesh	0.025	0.024	0.018	0.025	0.025
Delhi	0.248	0.208	0.285	0.198	0.177
Gujarat	0.039	0.170	0.116	0.037	0.089
Haryana	0.022	0.012	0.024	0.010	0.013
Karnataka	0.048	0.024	0.018	0.034	NA
Maharashtra	0.142	0.190	0.117	0.140	0.165
Punjab	0.010	0.027	0.014	0.003	0.025
Tamil Nadu	0.096	0.068	0.087	0.099	0.051
Telangana	0.040	0.040	0.032	0.130	0.114
Uttar Pradesh	0.096	0.042	0.069	0.034	NA
West Bengal	0.077	0.049	0.032	0.201	0.101

Appendix F. Upstreamness

In order to measure how consumer-facing a company is, we follow Kisat and Phan (2020) and use a measure of how upstream the industry is in the global value chain, based on its industry code. "Upstreamness," standard in trade and network literature, captures a "distance from final use" (Antràs et al. 2012), and is measured at the industry-level using a country's input-output table. In brief, the gross output Y of each industry j is defined as the sum of its final goods (F_j) and intermediate goods (Z_j) that are used as inputs in other industries $\neg j$. Z_j can then be disaggregated as all the dollar amount of industry j's output that is needed to produce industry k's output (Y_k), summed over all industries $k \neq j$. This quantity can similarly be disaggregated into an infinite sum of its inputs further along the supply chain.

$$Y_j = F_j + Z_j = F_j + \sum_{k=1}^{N} d_{jk} Y_k = F_j + \sum_{k=1}^{N} d_{jk} F_k + \sum_{k=1}^{N} \sum_{l=1}^{N} d_{jk} d_{kl} F_l + \dots \tag{A1}$$

An industry's upstreamness U_j is measured then as the sum of each of the terms in equation A1 multiplied by its distance from final use and divided by Y_j:

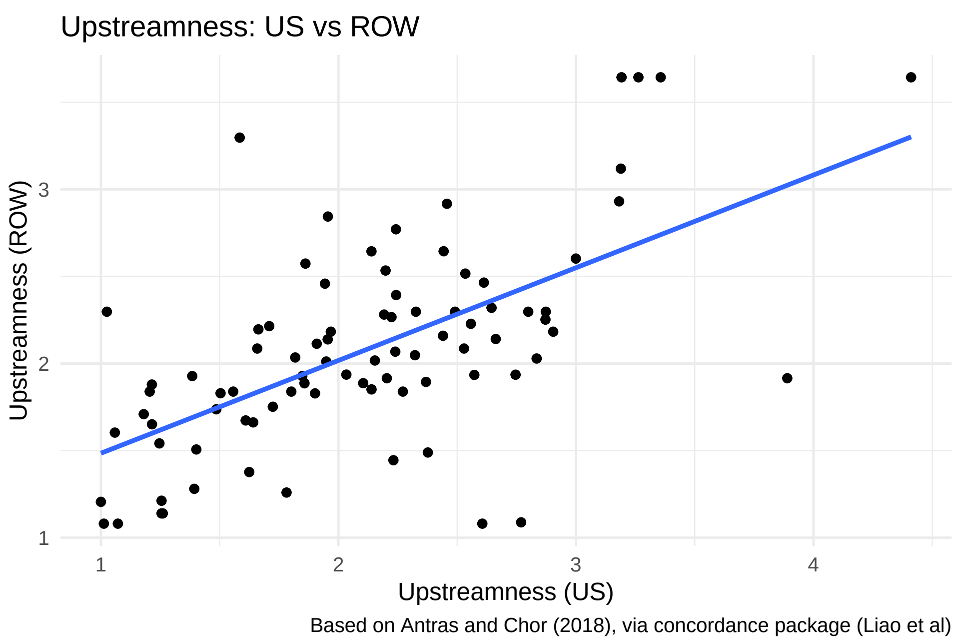
$$U_j = 1 \cdot \frac{F_j}{Y_j} + 2 \cdot \frac{\sum_{k=1}^{N} d_{jk} F_k}{Y_j} + 3 \cdot \frac{\sum_{k=1}^{N} \sum_{l=1}^{N} d_{jk} d_{kl} F_l}{Y_j} + \dots \tag{A2}$$

This produces an intuitive result where $U_j \geq 1$ and when U_j is close to 1 it is more downstream and consumer-facing (e.g. automobiles and footwear sectors) and for higher values, the industry is farther away from being consumer facing (e.g. petrochemicals and refining of copper).

Antràs and Chor (2018) compute and share a measure of upstreamness for 4-digit ISIC industries for 41 countries at various points of time using the World Input Output Database.[21] As India is not one of the countries, we use the measure of upstreamness for the catchall Rest of World category. We also use upstreamness based on the United States as a robustness check—these two measures are highly correlated (see appendix A5).

[21] We access this measure through the `concordance` package in R (Liao et al. 2020).

FIGURE A5. Upstreamness ROW vs Upstreamness USA



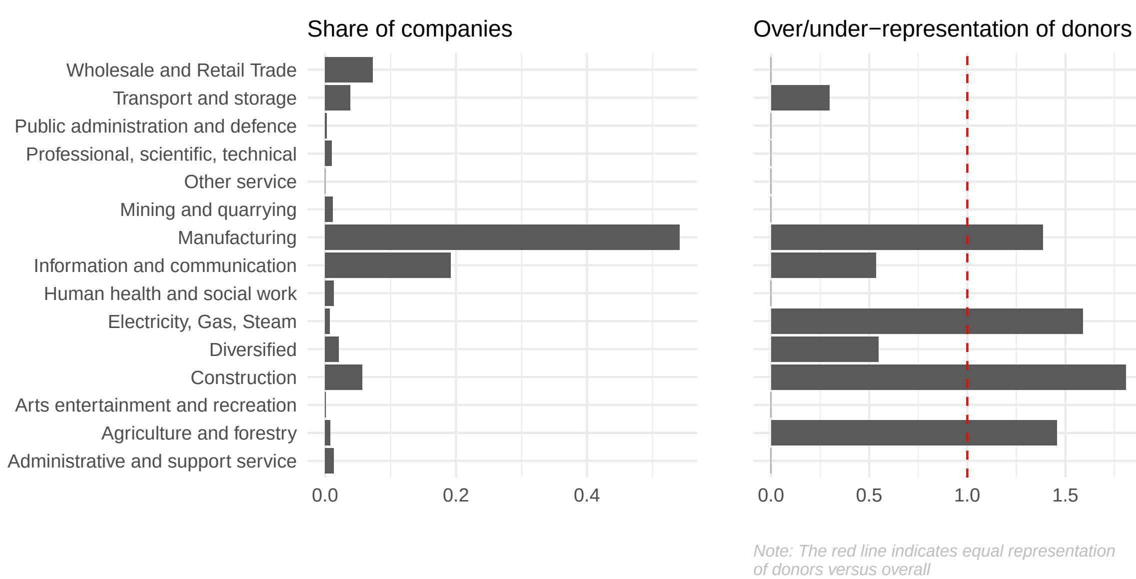
Appendix G. Donor Status Covariates

TABLE A1. Correlations with Donor Status

	(1)	(2)	(3)	(4)	(5)
(Intercept)	−0.195	−0.368	0.052	0.057	−0.331
	(0.031)	(0.049)	(0.009)	(0.006)	(0.054)
log(marketcap)	0.024				0.011
	(0.003)				(0.005)
log(total_assets)		0.025			0.017
		(0.003)			(0.006)
leverage			0.000		0.000
			(0.000)		(0.000)
return_on_equity				0.000	0.000
				(0.000)	(0.000)
Num.Obs.	1537	1537	1537	1537	1537
R2	0.044	0.047	0.000	0.000	0.050

Standard errors in parentheses

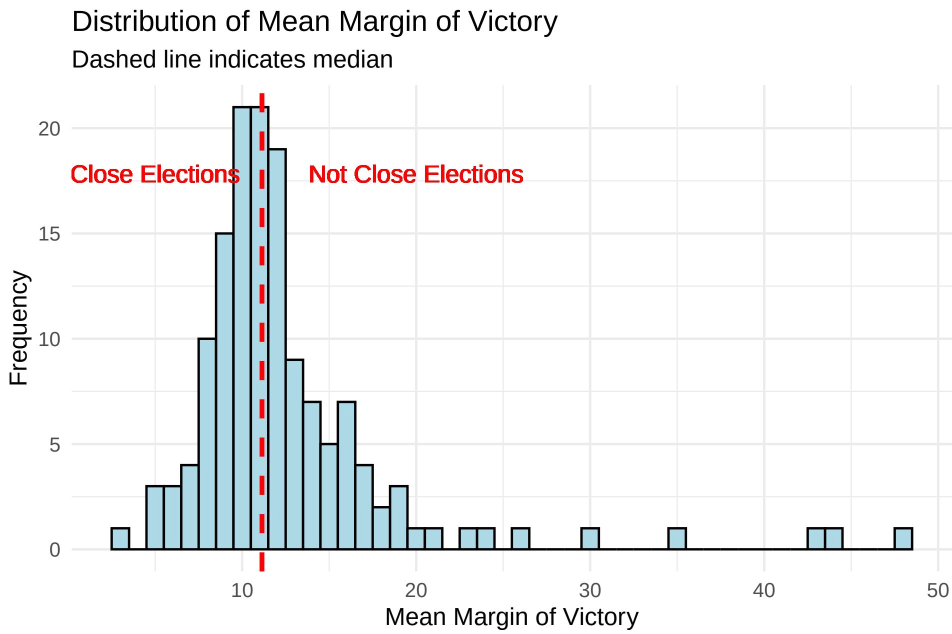
FIGURE A6. Sector distribution



Note: The left panel represents the sectoral distribution of all companies traded on the National Stock Exchange. The right panel shows the sectoral distribution of publicly listed donors relative to the overall sectoral distribution. Manufacturing, utilities (electricity, gas, steam), construction, and agricultural sector companies are overrepresented as donors. Sectors represent NIC "Section" divisions.

Appendix H. Margin of Victory

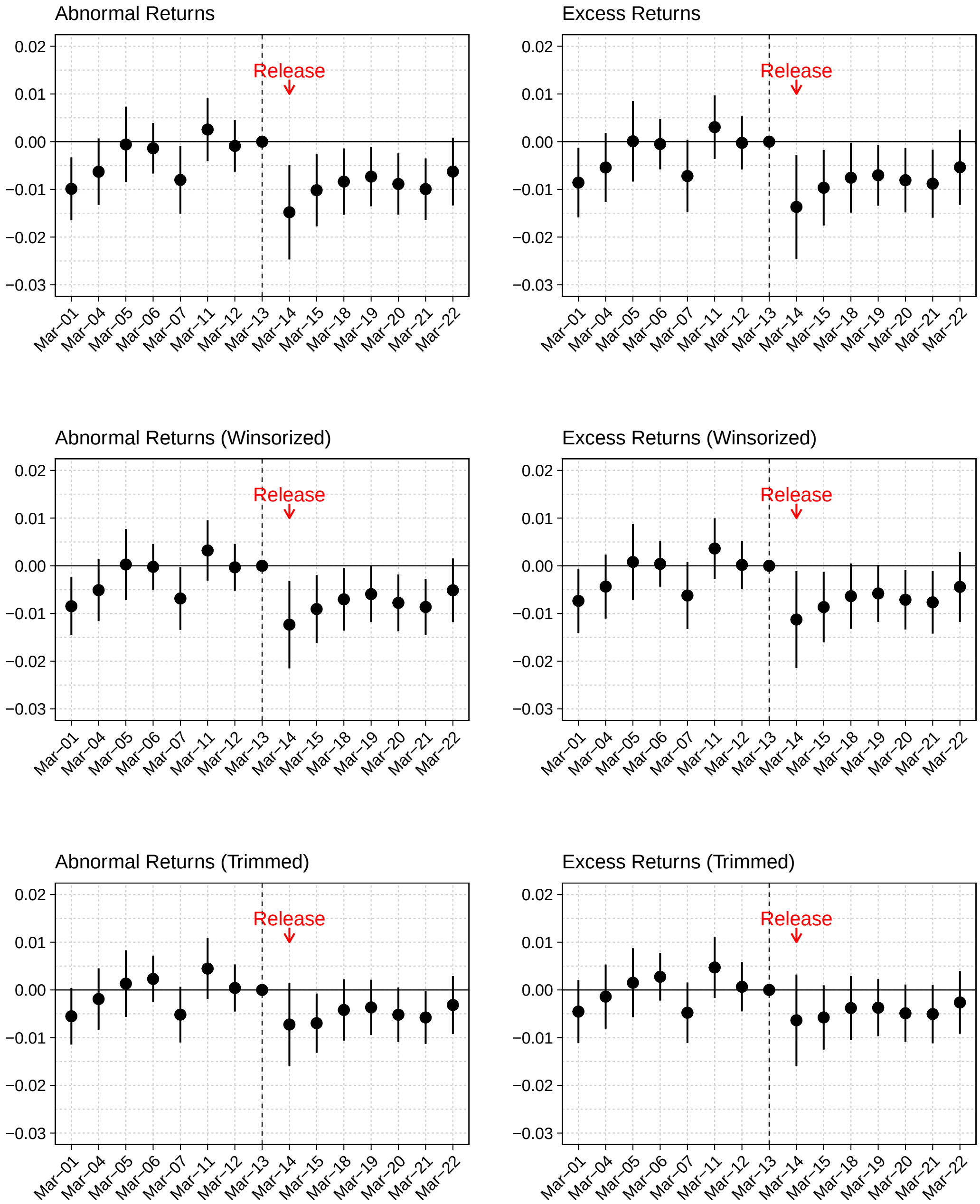
- India has single-member district FPTP elections.
- Margin of Victory: $\text{MOV}_d = \text{VoteShare}_{1st} - \text{VoteShare}_{2nd}$ in district d
- Mean MOV per state-election: $\overline{\text{MOV}}_{s,e} = \frac{1}{N}\sum_d \text{MOV}_d$
- "Close election" defined as $\overline{\text{MOV}}_{s,e}$ below median



Appendix I. Event Study

I.1. Plots

FIGURE A7. Daily Returns Event Study Plots



Note: Winsorizing and trimming daily returns ensures results are not driven by outliers. Winsorized: Daily returns less than the first percentile or greater than the 99th percentile of daily returns capped to the 1st or 99th percentile. Trimmed: Daily returns restricted to 1-99th percentile of daily returns.

I.2. Tables

TABLE A2. Daily Return Event Study

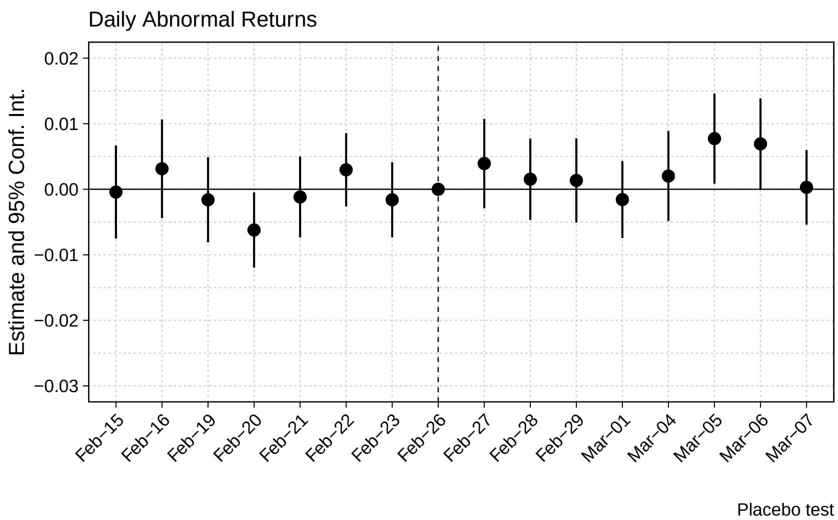
	Abnormal Return			Excess Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Mar-01 × is_donor	−0.011	−0.009	−0.007	−0.010	−0.009	−0.006
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Mar-04 × is_donor	−0.005	−0.004	−0.001	−0.004	−0.003	0.000
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Mar-05 × is_donor	−0.005	−0.004	−0.002	−0.005	−0.004	−0.002
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Mar-06 × is_donor	−0.001	0.000	0.002	−0.001	0.000	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mar-07 × is_donor	−0.009	−0.008	−0.006	−0.009	−0.008	−0.006
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Mar-11 × is_donor	0.002	0.003	0.004	0.003	0.003	0.004
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mar-12 × is_donor	0.001	0.001	0.001	0.001	0.001	0.002
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Mar-14 × is_donor	−0.015	−0.013	−0.009	−0.014	−0.013	−0.009
	(0.005)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)
Mar-15 × is_donor	−0.010	−0.009	−0.007	−0.010	−0.009	−0.006
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Mar-18 × is_donor	−0.007	−0.006	−0.003	−0.007	−0.006	−0.003
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Mar-19 × is_donor	−0.007	−0.006	−0.004	−0.007	−0.006	−0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mar-20 × is_donor	−0.008	−0.007	−0.005	−0.008	−0.007	−0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mar-21 × is_donor	−0.010	−0.009	−0.006	−0.010	−0.008	−0.005
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
Mar-22 × is_donor	−0.007	−0.006	−0.005	−0.006	−0.005	−0.005
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
Modification		Winsorized	Trimmed		Winsorized	Trimmed
Num.Obs.	23 055	23 055	22 440	23 055	23 055	22 447
R2	0.317	0.339	0.331	0.301	0.321	0.311
Std.Errors	by: isin	by: isin	by: isin	by: isin	by: isin	by: isin
FE: ISIN	✓	✓	✓	✓	✓	✓
FE: Trading Day	✓	✓	✓	✓	✓	✓

Note: OLS estimation based on equation 2, with period dummies interacted with total assets, leverage, return on equity, market cap, and NIC product section for each firm. Firm financial data as of September 30, 2023. Market cap is as of Feb 15, 2024. Firm-clustered standard errors reported in parentheses.

I.3. Placebo Test

Replace event date with a placebo date from two weeks before the information shock. I choose Feb 26 as the reference date. Figure A8 shows no systematic pattern of difference in abnormal returns between firms revealed on the list of donors and not.

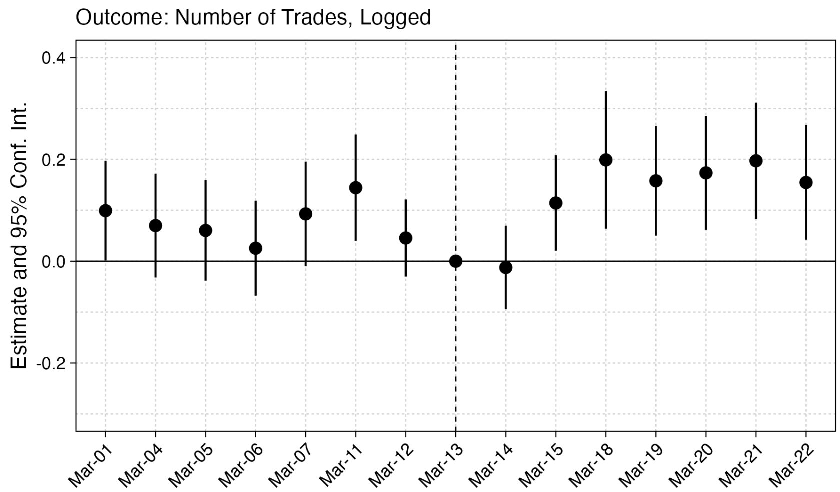
FIGURE A8. Event Study Placebo Test



Note: 95% confidence interval. Size, leverage, profits, market capitalization (as of Feb 15, 2024) and industry sections all interacted with time dummies.

I.4. Trading Volumes

FIGURE A9. Number of Trades



Note: 95% confidence interval. Size, leverage, profits, market capitalization (as of Feb 15, 2024) and industry sections all interacted with time dummies.

Appendix J. Cumulative Abnormal Returns

J.1. CATT on Cumulative Abnormal Returns

TABLE A3. CATT on Cumulative Abnormal Returns

	1	2	3	4	5	6	7	8	9	10
Post x Donor	−0.015	−0.017	−0.016	−0.015	−0.015	−0.017	−0.015	−0.006	−0.005	−0.004
	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
R2	0.652	0.653	0.649	0.644	0.625	0.643	0.649	0.618	0.591	0.565
Trading days	1	2	3	4	5	6	7	8	9	10
Num Stocks	1537	1537	1537	1537	1537	1537	1537	1537	1537	1537

Firm-clustered standard errors in parentheses

Appendix K. Synthetic Control Method

K.1. Approach

I follow Acemoglu et al. (2016), given its similar setting of multiple treated units, and aggregate treated firms' actual returns deviations from their synthetic counterfactuals. I estimate confidence intervals using permutation tests as recommended by Abadie et al. (2010); Abadie (2021).

The principle behind this approach is to construct a synthetic match for each treated unit by weighting "donor" (i.e. control) units such that pre-event trends are similar. After constructing such a match, the effect of the event is simply the deviation in behavior between the actual treated unit and its synthetic pair. This calculates a treatment effect for each treated unit individually. I calculate control unit weights over an estimation period of one year, ending one month before the event date.

Formally, I construct a synthetic match for each treated firm i given each control firm j by solving the following optimization problem:

$$\begin{aligned} &\underset{w_j^i}{\arg\min} \quad \sum_{t \in \text{Estimation window}} \left[R_{it} - \sum_j w_j^i R_{jt} \right]^2 \\ &\text{s.t.} \quad \sum_j w_j^i = 1 \quad \text{and} \quad w_j^i \geq 0 \end{aligned} \tag{A3}$$

where R_{it} is the daily return for treated company i on date t during the estimation window. w_j^i is the weight of control unit j that is calculated in this optimization problem. $\sum_j w_j^i = 1$ and $w_j^i \geq 0$ ensure non-negative weights that sum to 1.

After optimal weights are calculated, I calculate synthetic returns for each treated unit i with the following equation:

$$\hat{R_{it}} = \sum_j w_j^i R_{jt}$$

And Abnormal Returns is simply the difference between actual returns and synthetic returns:

$$AR_{it} = R_{it} - \hat{R_{it}}$$

Estimating the effect of the event requires defining the event window: τ_1, τ_2. Note, aggregating across multiple treated units to calculate an average effect does not change the individual estimation procedures (Abadie 2021). The effect of revealing treated companies names is estimated as:

$$\hat{\Phi}(\tau_1, \tau_2) = \frac{\sum_{i \in \text{Treatment group}} \frac{\sum_{\tau_1}^{\tau_2} AR_{it}}{\sigma_i}}{\sum_{i \in \text{Treatment group}} \frac{1}{\sigma_i}}, \tag{A4}$$

where $\frac{1}{\sigma_i}$ is a goodness of fit that overweights better matches (similar in spirit to corrections recommended by Ben-Michael et al. (2021)). $\hat{\sigma}_i$ is defined as:

$$\hat{\sigma}_i = \sqrt{\frac{\sum_{t \in \text{Estimation window}} \left(R_{it} - \hat{R}_{it}\right)^2}{T}} \tag{A5}$$

where T is the length of the estimation window (for me, 250 days).

Finally, I take a permutation approach to calculating confidence intervals as recommended by Abadie et al. (2010) which involves calculating a test statistic and comparing how extreme this test statistic is compared to a distribution, and is followed by Acemoglu et al. (2016). I randomly draw 5000 placebo treatment groups from the set of control units. Each group is the same size as the actual treatment group (88 units). For each placebo group, I calculate a treatment effect over several days starting from the event date of March 14, 2024, $\hat{\phi}(\tau_1, \tau_2)$, and construct a distribution of placebo group effects. I compare the real treatment effect to this distribution. Since the hypothesized effect is negative, I conduct a one-sided hypothesis test where I evaluate if the real treatment effect is significant at 5% if it is below the 5th percentile of the placebo group distribution.

K.2. Results

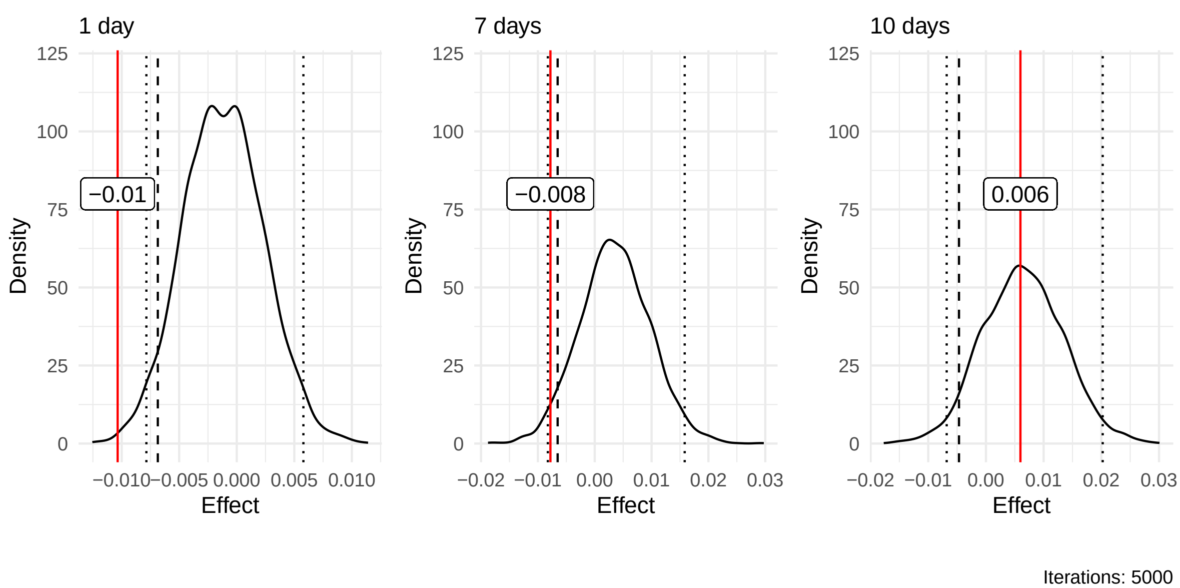


FIGURE A10. Cumulative Abnormal Returns: ATT against placebo

Appendix L. News Mentions

L.1. Data

I use `newsapi.org`, which provides a REST (representational state transfer) API to query current and historical news records from over 150,000 news sources from around the world in multiple languages. Each query returns the headline, a snippet, and a description of each article, along with authorship information, source, and language.

I carry out three sets of searches. First, I construct the *electoral bonds news corpus* by searching for the term "electoral bonds" between Jan 1, 2024 and April 30, 2024. This search produces around 1,200 search results all related to India's electoral bonds. Panel A in figure A11 shows how articles that meet this search term spike around key dates: the supreme court decision as well as the release date.

Second, I construct a *reference news corpus* by searching for news articles that contain the terms "elections" and "India" between Jan 1, 2024 and April 30, 2024. I include "India" to restrict the geography to India, as `newsapi.org` does not allow geographic filters in setting search parameters.

Finally, for each treated company revealed to be a donor, I search for news that contains the name of the firm and "electoral bonds", and filter for the period from March 14-28, 2024.

L.1.1. News Text Analysis

I compare the *electoral bonds news corpus* to the *reference news* corpus by computing the term frequency-inverse document frequency (TF-IDF) for key terms in each corpus, and calculating a ratio between each corpus's TF-IDFs.

$TF-IDF_{ij}$ for each term i in corpus j is defined as the product of Term Frequency (TF_{ij}) and Inverse Document Frequency (IDF_{ij}). TF_{ij} is the count of occurrences of i in corpus j. IDF_{ij} is the log of one over the share of documents in corpus j that contain the term i.

Per Gentzkow et al. (2019), TF-IDF filters out both very rare and very common terms because TF_{ij} will be low for extremely rare terms, and IDF_{ij} will be low for extremely common terms that are present in all documents.

The TF-IDF ratio is defined for each term as:

$$\text{Ratio}_i = \frac{\text{TF-IDF}_{i,j=\text{Electoral Bond News}}}{\text{TF-IDF}_{i,j=\text{Reference News}}} \tag{A6}$$

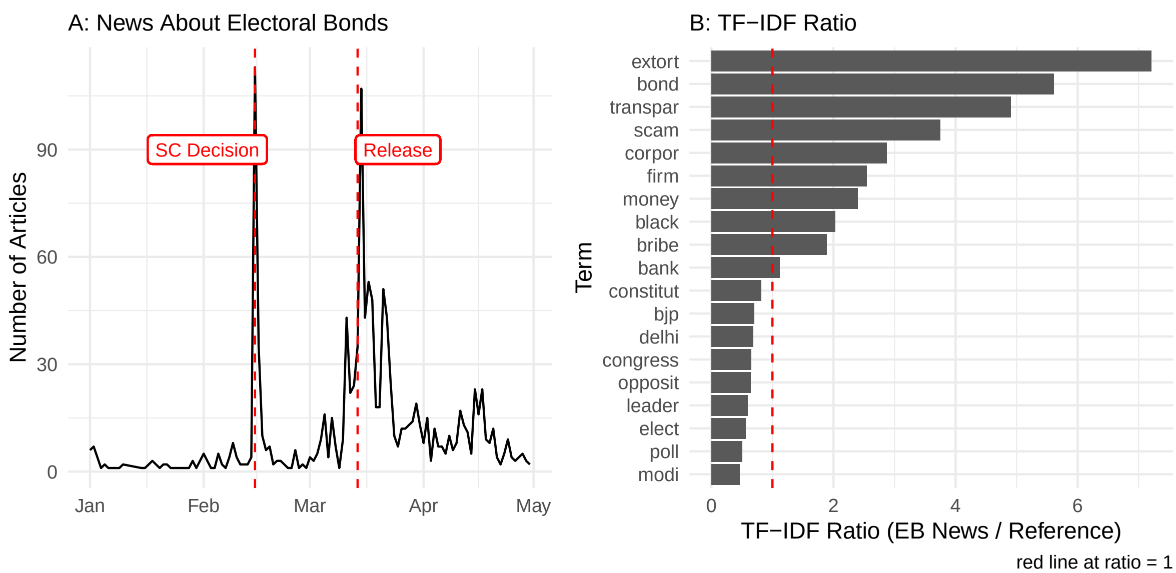
Table A4 presents the statistics.

L.2. Visualization

TABLE A4. TF-IDF Comparison

Term	EB News TF-IDF	Reference News TF-IDF	Ratio
extort	61.05	8.47	7.21
bond	325.32	58.00	5.61
transpar	108.47	22.10	4.91
scam	82.94	22.10	3.75
corpor	81.57	28.43	2.87
firm	81.20	31.87	2.55
money	129.58	54.00	2.40
black	58.26	28.78	2.02
bribe	12.46	6.60	1.89
bank	179.57	160.09	1.12
constitut	72.57	88.98	0.82
bjp	299.25	425.54	0.70
delhi	143.57	208.94	0.69
congress	267.01	409.84	0.65
opposit	120.17	187.31	0.64
leader	144.03	240.75	0.60
elect	252.90	451.05	0.56
poll	182.13	359.39	0.51
modi	198.07	429.46	0.46

FIGURE A11. News Coverage About Electoral Bonds



Note: Panel A shows the count of news articles mentioning electoral bonds, from `newsapi.org`. Panel B reports, for specific terms, the ratio of TF-IDF between the corpus of news mentioning electoral bonds and a reference corpus of news about elections and India. A ratio greater than 1 indicates the term being more prominently mentioned in electoral bond coverage than in general elections-related news.

Appendix M. Raids

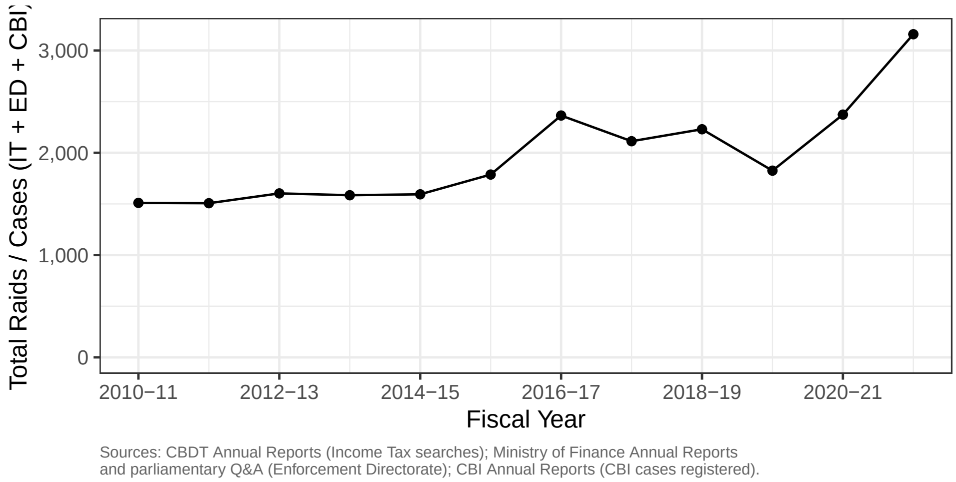


FIGURE A12. Central Government Agency Raids Over Time

Note: This figure shows the number of raids conducted by central government investigative agencies (Enforcement Directorate, Central Bureau of Investigation, Income Tax Department) over time.