The Executive Unbound: Politicized Bureaucracy and Partisan Procurement under DOGE*

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September 4, 2025

Abstract

The establishment of the Department of Government Efficiency (DOGE) during Trump's second term marks an expansion of presidential authority over federal agencies. This institutional development provides a rare opportunity to examine whether presidents can leverage politicized agencies for political and electoral goals. Drawing on detailed procurement data and DOGE's cancellation records, we find that Republican donor firms were less likely to face cancellations, whereas firms donating to Democrats were more likely to lose contracts. Cancellations were less frequent in Republican-held districts, conservative agencies, and states favorable to the Republican Party. Leveraging the timing of the 2025 Wisconsin Supreme Court election, we use a difference-in-differences design to show that Wisconsin-based firms experienced a sharp increase in cancellations following the election, underscoring the strategic timing of DOGE's operations. Our findings shed new light on the consequences of agency politicization and align with the Trump administration's effort to consolidate its support base.

Word count: 10,135

*For helpful comments, we are thankful to Brandice Canes-Wrone, Carlo Prato, Jon Rogowski, Hye Young You, and seminar participants at Stanford University and the Princeton-Seoul National University Summer Institute.

Introduction

A longstanding argument in the literature on the American presidency is that presidents seek to run bureaucracies "through hands-on management and control" (Moe 1989, 280). To that end, presidents attempt to centralize power inside the Executive Office of the President, and choose political appointees who are willing to follow presidents' leadership and implement their policy agenda (Heclo 1977; Moe 1985; Rudalevige 2002). These politicized agencies are generally considered more responsive to the policy preferences of presidential administrations (e.g., Moe 1982; Wood and Waterman 1991; Bolton, Potter, and Thrower 2015; Lowande 2019), although responsiveness may come at the cost of expertise and performance (Lewis 2008; Krause and O'Connell 2019).

Besides helping presidents achieve their policy goals, scholars have long raised concerns that politicized agencies may be used to advance presidents' own political and electoral goals. A growing body of empirical evidence supports this view, showing that presidents can direct agency resources toward key electoral constituencies and political supporters (e.g., Berry, Burden, and Howell 2010; Rogowski 2016; Krause and Zarit 2022; Lee 2025), especially when agencies are led by political appointees co-partisan with the President (Berry and Gersen 2016; Dahlström, Fazekas, and Lewis 2021; Moskowitz and Rogowski 2025). Yet a smaller set of studies has highlighted the potential limitations of politicized agencies carrying out these efforts—whether due to agency problems between political principals and bureaucrats, or the limited scope of government resources that agencies can deploy as particularistic benefits (Gordon 2011). Albeit important, assessing the effectiveness of presidents' efforts to steer politicized agencies remains challenging, in part due to the difficulty of identifying empirical settings where the president explicitly attempted to control the bureaucracy for her own political goals.

The establishment of the Department of Government Efficiency (hereafter, DOGE) at the outset of the second Trump administration reinvigorates the debate about the political consequences of agency politicization and offers a unique opportunity to study the role of politicization as a potential mechanism for directing benefits in ways that suit the president's political goals. DOGE represents a novel institutional expansion of presidential authority over federal agencies, and one of the most disruptive efforts ever attempted to circumvent the constraints of a professionalized bureaucracy in order to pursue the president's priorities. In this paper, we examine the extent to which such a highly politicized agency can effectively deliver on the president's political and electoral objectives. Using detailed procurement data and snapshots of DOGE's contract cancellation records, we assess whether—and how—DOGE engaged in sophisticated and politically motivated contract cancellations, rewarding allies and punishing foes of the president.

DOGE's significance lies in three exceptional features. First, DOGE is an unusually politicized agency, reportedly staffed with only a few loyal Trump appointees and lacking the typical government experience found among career bureaucrats. Second, although DOGE has an acting commissioner, it was *de facto* directed by Elon Musk, a "special government employee" known for his hostility toward government oversight. Third, DOGE progressively extended its operational reach by creating DOGE-controlled units within key agencies and departments. This muddled authority structure complicates congressional oversight, making it difficult for Congress to scrutinize DOGE's decision-making processes. Although no agency like DOGE has existed before, its creation may serve as a precedent for future presidents seeking to set up similar institutions. Studying DOGE's operations thus provides a rare opportunity to assess whether such a highly politicized agency is effective at carrying out the president's goals.

Empirically, we focus on DOGE's initiative to cut government spending. To that end, DOGE terminated thousands of procurement contracts awarded by federal agencies, resulting in an estimated (and self-reported) $34 billion in savings.[1] To assess whether DOGE effectively advanced President Trump's political and electoral goals, we analyze patterns in its contract cancellations. Although DOGE was ostensibly created to improve government efficiency, anecdotal evidence suggests that political motives may underlie its initiatives. For one, anonymous interviews revealed that DOGE employees extensively worked on terminating contracts awarded to Harvard University for earthquake relief research, and contracts awarded to the

[1]See doge.gov/savings, accessed June 13, 2025.

state of Maine, as Trump had escalated fights with the university and the state (Flavelle et al. 2025). Moreover, when Musk and Trump parted ways at the end of May 2025, the former faced similar threats of contract termination, as Trump vowed to revoke billions of dollars in federal contracts and tax subsidies for Musk's business empire (Pager 2025). Such politically motivated actions associated with government procurement are consistent with a substantial body of literature demonstrating how presidents utilize federal contracts to reward political allies and consolidate electoral support among key constituencies (Gordon 2011; Kriner and Reeves 2015; Dahlström, Fazekas, and Lewis 2021; Lee 2025).

In our analyses, we examine active contracts as of January 20, 2025, to assess which ones DOGE canceled and whether this cancellation reflects efforts to reward political allies and punish opponents. To identify DOGE-terminated contracts, we program a semi-daily scraper to build a high-frequency picture of DOGE contract termination over time, collecting data directly from the DOGE website. As of June 30, 2025, DOGE terminated 1.4% of the 545,459 contracts we analyze, with peaks of cancellations between the second half of February and the first half of March, 2025.

To identify political allies and adversaries of the Trump administration, we focus primarily on campaign contributions made by firms linked to the contracts. Our focus on campaign contributions as a presidential interest is based on a large literature that portrays presidents as chief fundraisers for their party (Jacobson, Kernell, and Lazarus 2004), and ample anecdotal evidence that shows how Trump uses campaign donations—which is visible and public information—as a key criterion for distinguishing friends from foes. A notable example is his withdrawal of Jared Isaacman's nomination for NASA Administrator after discovering that the billionaire entrepreneur—despite being a close associate of Elon Musk—had donated to Democratic candidates in the previous two election cycles (Swan, Haberman, and Chang 2025).[2] To capture firms' donations to the Republican and Democratic parties, we match awarded firms with campaign finance records for the election cycle 2023-24. This data allows us to establish

[2]Beyond government contracts, anecdotal evidence highlights Trump's administration systematic attempt at mapping friends and enemies, such as the corporate loyalty scorecard that ranks hundreds of companies and trade associations by how strongly they supported the president's One Big Beautiful Bill (Allen 2025), or the targeting of law firms deemed as dishonest and detrimental to American interests (Schmidt 2025).

several stylized facts about donor firms and public procurement: *i)* just above 2% of firms awarded an active government contract donate to a candidate or committee in 2024; *ii)* albeit few in numbers, donor firms receive a disproportionate share of federal contracts (firms with a large number of awarded contracts are 15 times more likely to donate); and *iii)* donor firms exhibit a clear partisan pattern, donating substantial amounts of money to either the Democratic or the Republican Party.

We present two sets of analyses. First, we analyze contracts cross-sectionally to establish whether contracts awarded to firms donating to the Republican (Democratic) party were less (more) likely to be terminated. The richness of procurement data allows us to make highly stringent comparisons between nearly identical contracts awarded by the same agency to firms located in the same congressional district and sharing similar observable characteristics, differing primarily in their campaign contribution records. Leveraging machine learning tools, we additionally hold constant the termination potential of contracts as inferred by the language used in their description. Furthermore, by controlling for various objective measures of contract-level inefficiencies, we are able to detect politically motivated contract cancellations based on firms' campaign contributions, regardless of DOGE's formal mission to cut wasteful government spending.

Our findings suggest three key patterns. First, DOGE engaged in politically sophisticated contract cancellations: contracts awarded to firms that made substantial contributions to the Republican Party were less likely to be canceled by DOGE, whereas those awarded to firms that donated larger amounts to the Democratic Party were more likely to be terminated. Second, such contract cancellations were contingent on political contexts that appeared especially important to the Trump administration. Termination rates were markedly lower in Republican-held congressional districts, in federal agencies with conservative missions, and in states electorally favorable to the Republican Party. In these cases, we find no detectable relationship between firms' campaign contributions and the likelihood of contract termination, suggesting that multiple factors—such as policy priorities and electoral geography—contributed to a calculated effort to avoid political backlash. Finally, our analysis of successive snapshots of terminated contracts shows that this pattern of contract cancellations emerged within just two months after DOGE's creation, indicating that the agency was able to act swiftly and decisively in benefiting the president's political base.

Our second analysis combines the dynamic nature of DOGE cancellation records with a natural experiment represented by the 2025 Wisconsin Supreme Court election to further demonstrate the political motives behind the cancellation of the DOGE contract. The Wisconsin judicial election, held on April 1, 2025, gained national attention as a crucial contest that would determine whether the Court's liberal majority would be upheld or replaced by a conservative one. In this context, Elon Musk and political groups aligned the Republican Party spent millions of dollars in supporting the Republican-backed and Trump-endorsed candidate, an election Musk himself described as "crucial for the destiny of humanity" (Schleifer 2025).

Leveraging the timing of the election and our detailed information on when DOGE posted contract terminations on its website, we implement a difference-in-differences design that compares the share of terminated contracts for Wisconsin-based firms to that of firms in other states before and after the April 1st Wisconsin election. Our results reveal that the share of terminated contracts among Wisconsin-based firms rises sharply after the election (won by the Democratic candidate), suggesting that political motives may underlie DOGE's contract cancellation decisions.

With this paper, we make three contributions to the literature. First, we contribute to the literature on American political institutions and presidential control over bureaucracies. While existing work generally assumes that Presidents seek to control bureaucracies, the establishment of DOGE represents an unequivocal context wherein President Trump used a newly created organization to reform the administrative state. Similarly, DOGE represents a case of a highly politicized agency and, hence, allows us to directly test whether politicization is an effective mechanism by which presidents can advance their own political goals. Our analysis indeed demonstrates how swiftly and effectively contemporary presidents can leverage politicized agencies as political instruments to advance their goals.

Second, we make two contributions to the literature on money in politics and the potential for corporate money to secure political favor. While most empirical evidence used to determine whether corporate money buys political favors focuses on roll calls (e.g., Folwler, Garro, and Spenkuch 2020) or stock market prices (Cooper, Gulen, and Ovtchinnikov 2010), our analysis of procurement contracts represents a more direct connection between firms' political giving and the receipt of political favors. In addition, our findings shed light on the conditions under which corporate money may secure political favor, a longstanding question in the literature on money in politics. While prior empirical evidence on this question has been mixed (e.g., Stratmann 2005; Ansolabehere, Figueiredo, and Snyder 2003; Grier, Grier, and Mkrtchian 2023), our results suggest that such quid pro quo exchanges via corporate political giving may be conditional on other political contexts such as policy priorities or geography. For one, even if firms have not contributed significantly, incumbent politicians might still provide benefits to them if they are located in districts controlled by the incumbents' co-partisan legislators or in areas of strategic interest to the party. Our findings underscore the importance of researchers considering multiple layers of political connectedness when examining the returns on corporate political spending.

Finally, this paper contributes to the growing body of literature on the policy consequences of populism. While prior research on populism and bureaucracy highlights how President Trump sought to sabotage federal agencies (Bauer and Becker 2020), appointed less competent bureaucrats (Lewis and Richardson 2021), and aimed to dismantle civil service protections (Moynihan 2022), our findings demonstrate that populist leaders can also effectively deploy a politicized bureaucracy staffed with loyalists to pursue their electoral goals and claim credit for allegedly fulfilled campaign promises (Canes-Wrone, Herron, and Shotts 2001; Bellodi et al. 2023; Lowande 2024). Our focus on government contracts highlights yet another tool that populist politicians can use to advance their agenda.

Institutional Context: DOGE and Federal Contracting

DOGE was established shortly after Donald Trump's second inauguration on January 20, 2025, following a discussion between Trump and Elon Musk in the summer of 2024 about forming a new presidential commission on "government efficiency" (Sullivan, Duffy, and Bradner 2024). To swiftly install DOGE within the executive branch, the Trump administration did not need to create a new agency. Instead, they reorganized and renamed the U.S. Digital Service as the U.S. DOGE Service (USDS) and established it inside the Executive Office of the President (The White House 2025).

Although DOGE has an acting commissioner, it was widely acknowledged that, until his departure in late May, DOGE was run by Elon Musk and a team of young engineers he had recruited (Elliott 2024). This opaque leadership structure has made it difficult for Congress to monitor the actions of DOGE and to determine exactly who comprises DOGE's staff and management—a lack of transparency that has drawn criticism from several commentators, some of whom argue that the opacity was intentional (Williams 2025).

Since its inception, one of DOGE's official missions has been to reduce wasteful spending by canceling a substantial number of federal contracts, grants, and leases. Despite its official mission of cutting waste, questions have been raised about whether DOGE is genuinely working to improve government efficiency or instead serving as a tool for ideological purges on behalf of the Trump administration (e.g., Bonica 2025). Political commentators referred to DOGE as the "Department of Government Control", suggesting it wields enormous power to reward political allies and punish opponents (Klein 2025).

Among the initiatives led by DOGE, we focus on its efforts to target federal contracts. Federal contract-level data in the U.S. provides detailed information associated with each contract, which may be used to identify various political allies or adversaries. Leveraging this rich data source, scholars have shown that federal contracts are more likely to be awarded in areas where presidents seek to gain additional votes—for example, congressional districts where the president's party needs to win seats (Gordon 2011) or in presidential battleground states (Dahlström, Fazekas, and Lewis 2021). Presidents may also instruct agencies to favor areas with senators with proximate ideologies (Bertelli and Grose 2009). Additionally, decisions to award federal contracts have been found to be influenced by corporate political contributions (Fazekas, Ferrali, and Waches 2023; Lee 2025). Federal contracting thus provides us an opportunity to examine how contract decisions could be influenced by various indicators of political friends and allies.

Data

Our analysis combines three sources of data. First, we construct a sample of active contracts (not yet terminated) as of January 20th, 2025, the inauguration day of the second Trump administration. Second, we obtain dynamic snapshots of the set of contracts terminated by DOGE, as posted on DOGE's website. Finally, we use campaign contribution data to measure the donation behavior of firms associated with active contracts.

Active Procurement Contracts

To understand DOGE's motives, we need to examine which contracts were terminated among all active contracts as of January 20th, 2025. To do so, we obtain all federal contracts signed from fiscal years 2004 to 2025 from the Federal Procurement Data System (FPDS).[3] FPDS provides detailed information on the universe of federal contracts, including modification records and the date when awarding agencies expect the contract to be completed.

We use two criteria to determine whether contracts were still active as of January 20th, 2025. First, contracts are considered terminated if they include modification records such as: "close out," "termination for convenience (complete or partial)," "legal contract cancellation," "termination for cause," or "termination for default (complete or partial)." Second, contracts are considered terminated if their latest expected completion date was before January 20th, 2025. In such cases, even if the contracts are not explicitly and formally labeled as terminated, they are marked as completed in the federal procurement database.

We recover a total of 705,035 active contracts. Following standard practice in the procurement literature, we exclude active Indefinite Delivery Vehicles (IDVs), which are agreements without ex-ante specified quantities and deadlines. We also exclude contracts awarded to gov-

[3] Contracts signed earlier were mostly not reported in FPDS. Nonetheless, very few contracts signed in earlier years were still active as of January 20th, 2025. Table A.2 in the Appendix shows the number of contracts signed in each fiscal year. Only 3% of the total number of active contracts were signed before 2020, and 59% were signed in fiscal year 2024.

ernment entities and contracts performed outside the United States.[4] After applying these sampling restrictions, we obtain 545,459 awards that were performed in the United States and are still active as of January 20th, 2025.[5]

FPDS allows us to observe a rich array of characteristics of active contracts. First, our sample of contracts covers 71 federal agencies and 55,202 awarded firms. The agencies with the largest number of contracts are the Department of Defense (53% of the sample), the General Services Administration (10% of the sample), and the Department of Veterans Affairs (8% of the sample). Given the large share of defense contracts, the firms with the largest number of awards operate all in that industry: Noble Logistics LLC (2.5% of the sample), Atlantic Diving Supply Inc. (1.7% of the sample), and Boeing (1.5% of the sample).

Second, besides financial information for each contract (e.g., total value and total amounts already disbursed), each contract is assigned a transaction description, an industry code (NAICS), and a product or service code, such as "medical and surgical instruments", "airframe structural components", "office supplies", or "air conditioning equipment".[6] In the aggregate, agencies award contracts associated with 2,281 unique product codes and 1,088 unique NAICS code. There is also significant variation in products and services awarded within each agency. On average, agencies award contracts with 131 different industry classifications and 196 different product codes.

DOGE Terminated Contracts

Contracts terminated by DOGE are posted on its website under the *Wall of Receipts*.[7] The data include information on the federal agency that awarded the contract, the recipient firm's name, a brief contract description, the date when the canceled contract was uploaded on the website, the total awarded amount, and the savings resulting from termination. Importantly for our purposes, each contract also includes a URL that redirects to the contract's entry in the

[4] We do so given our analysis compares contracts performed in the same congressional district, but we show in the Appendix that the results are robust to including these awards (see Table G.11).

[5] Table A.1 in the Appendix shows the number of remaining contracts after each round of sample restriction.

[6] NAICS codes are provided by firms when they register in the federal procurement database. In contrast, product and service codes are assigned by federal agencies based on the goods or services they intend to procure. Almost all product and service codes are associated with multiple NAICS codes, and vice versa.

[7] See doge.gov/savings and Figure B.1 for an example.

Federal Procurement Data System (FPDS).[8]

We began scraping the data on February 26, 2025—just about one month after the first terminated contract was posted online. We took a snapshot of the data from the website almost every day since February 26, 2025 until June 30, 2025, resulting in a total of 71 snapshots.[9]

Taking daily snapshots of the DOGE website provides a unique view of the evolution of DOGE's contract-termination activity. The blue squares in Figure 1 show the total number of terminated contracts in each snapshot with a valid FPDS URL. The number ranges from 2,298 on February 26th to 8,021 on June 30, 2025, with the lowest number recorded on April 8th, at 690 terminated contracts. The reason for the sudden drop in April is largely because DOGE redacted information on contracts awarded by the U.S. Agency for International Development (USAID), and some contract-specific details were reported as "unavailable for legal reasons." The orange bars show the number of newly terminated contracts in each snapshot relative to the previous one. The day with the largest number of newly added contracts is March 1, with 1,493 newly added terminated contracts.

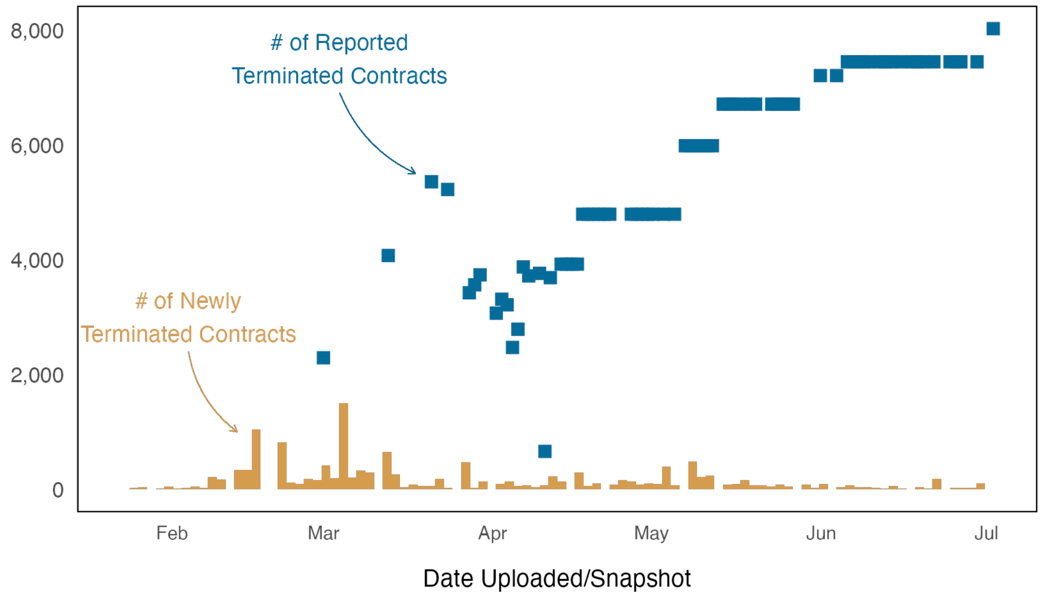
One advantage of our data collection process is that it allows us to capture contracts targeted by DOGE that are posted online at various points in time and later removed for various reasons. In fact, we find that, even excluding the very large drop in terminated contracts of April 8th, 56% of contracts initially posted as terminated are removed at least once across the snapshots obtained. In addition to the legal issues involving USAID-awarded contracts, DOGE removed several entries from its website after observers identified errors in its reports—for example, reporting cancellations of contracts that had already been terminated.[10] These posted-then-removed contracts are systematically different from those that are never removed (see Table B.3 in the Appendix), and their omission would bias the sample of terminated contracts. It should be noted that, for the purpose of this study, we are interested in capturing whether DOGE targets a contract (by terminating it and posting it online), even though this

[8]Starting from March 21, DOGE began redacting information on contracts awarded by the U.S. Agency for International Development (USAID) and contract-specific information was reported as "unavailable for legal reasons." On average, 91% of contracts with missing FPDS links were awarded by USAID.

[9]Starting in mid-April, we download terminated contracts through the new DOGE API (https://api.doge.gov/docs).

[10]See, for instance, https://www.nytimes.com/2025/02/25/upshot/doge-spending-cuts-changed.html.

Figure 1: Stock and Flow of Terminated Contracts Over Time.



Notes: Number of terminated contracts with or without valid FPDS URL scraped from DOGE websites and DOGE API across multiple dates. On average, 91% of contracts without FPDS URL are awarded by USAID.

contract is not ultimately terminated or is removed from the DOGE website. Our data hence allows us to observe 13,415 contracts *ever* terminated by DOGE, providing a complete picture of DOGE targeting.

From the FPDS URL of each contract, we extract a combination of unique contract identifiers, including parent award ID, award ID, transaction number, and awarding agency code, which we use to merge this data with our sample of active contracts. Of the 13,415 DOGE-terminated contracts, we successfully matched 11,921 (89%) to the 705,035 active contracts. We reviewed the remaining 1,494 contracts with valid links and found that most were unmatched because they had been terminated before January 20, 2025. Finally, once imposing the sample restrictions to non-IDVs performed in the United States, we obtain 7,777 DOGE-terminated contracts out of 545,459 active awards. Since its inception and as of June 30, 2025, DOGE has terminated 1.4% of the universe of active awards performed in the United States. In terms of total contract potential value amount, DOGE-terminated contracts account for 1.3% (corresponding to $ 53 billion) of total contract potential value amount.

Firms' Campaign Contributions

As a primary indicator for identifying DOGE's political allies and opponents, we focus on firms' campaign contributions. This approach is motivated by extensive research on whether corporate money secures political favors, which focuses on campaign contributions due to their measurability and the direct role in supporting politicians' and parties' electoral prospects (see e.g., Ansolabehere, Figueiredo, and Snyder 2003; Roscoe and Jenkins 2005; Folwler, Garro, and Spenkuch 2020).

To track firms' contributions, we focus on the political giving of firms' political action committees (PACs), which are funded by voluntary donations from employees or shareholders. There are two main channels through which firm PACs make donations. First, PACs are allowed to contribute to candidates and committees within limits set by the Federal Election Commission (FEC). Second, since the 2010 Supreme Court decision in *Citizens United v. FEC*, firm PACs are allowed unlimited political expenditures, as long as they are not coordinated with a candidate's campaign. This led to the rise of Super PACs, which can accept unlimited contributions and spend freely to advocate for or against candidates.

We rely on two data sources for tracking firm PACs' campaign contributions: data provided by the Center for Responsive Politics/OpenSecrets (https://www.OpenSecrets.org), a nonpartisan organization working on electoral transparency, and the Database on Ideology, Money in Politics, and Elections (DIME) by Bonica (2024). A key advantage of OpenSecrets is its ability to trace political donations made by firms through their affiliated PACs. Once we match firms awarded procurement contracts with those included in the OpenSecrets data, we supplement the PAC donation records using DIME. While OpenSecrets conducts extensive work linking firms to their corresponding PACs, the company names it assigned to PACs often differ significantly from those in federal contracting data. By using contributor information from DIME donation records at the committee level, we are able to capture additional PACs that may not be detected through OpenSecrets alone.[11]

Combining OpenSecrets with Federal Election Commission (FEC) data, we extract the list

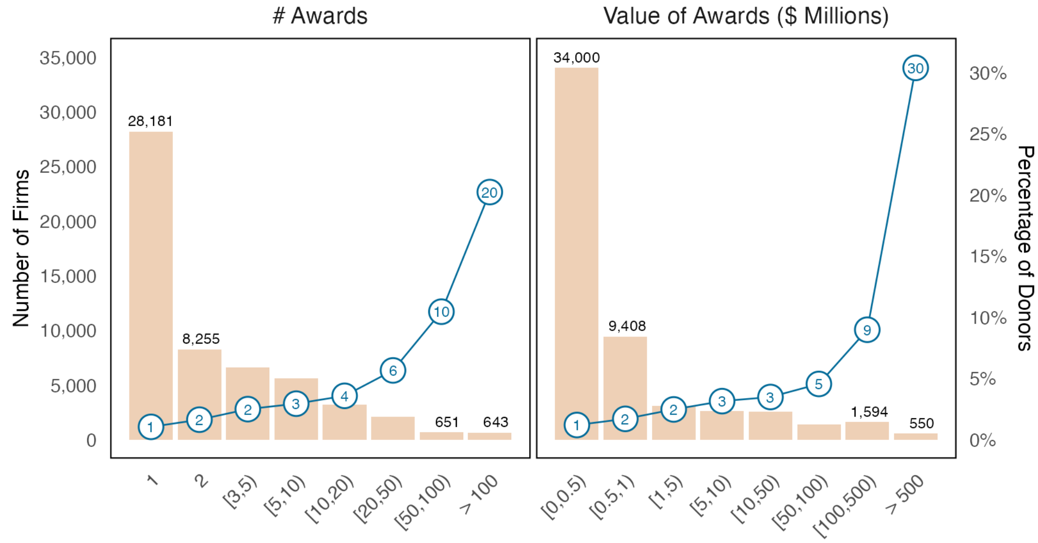
[11] Given our focus on firms, we do not include independent donations made by employees.

of firms with PACs that donated in the 2023-2024 election cycle. Then, we match these firms with parent firms in our sample of active contracts, using a combination of fuzzy name matching, large language models, and extensive manual checks and corrections. Appendix D provides a detailed description of our matching procedures.[12] Out of 55,202 unique parent firms in our sample of 545,459 active contracts, we match 1,183 of them—940 from OpenSecrets and an additional 243 from DIME—a match/donor rate of 2.1%. Such a small number of donor firms is consistent with accounts suggesting that there is little money in politics (e.g., Ansolabehere, Figueiredo, and Snyder 2003). Even though the vast majority of firms in federal contracting are small businesses with limited financial capacity, our share of donor firms aligns with findings on public firms' political giving. Cooper, Gulen, and Ovtchinnikov (2010), for instance, find that 9.49% of public firms made donations between 1979 and 2004, and Fouirnaies and Hall (2018) report that 95% of publicly traded firms in the U.S. have never contributed to a political campaign. Moreover, given that there were approximately 21,000 committees registered through the FEC in the 2024 election cycle, 1,183 donor firms is a sizable number of matched firms.

Our primary focus is on the amount of contributions made by these firm PACs to the Democratic and Republican parties. To track contributions, we first identify each firm's PAC by recovering its committee ID, then match it to FEC data to retrieve all transactions from that PAC to candidates and committees. Candidate partisanship is determined by linking candidate IDs to party affiliations recorded by the FEC. For committees, we assign partisanship through a three-step process. First, we use FEC-reported linkages between candidates and committees. Second, we classify the Republican and Democratic national committees accordingly. Third, using OpenSecrets, we identify Super PACs that—despite lacking formal party ties—primarily supported one presidential candidate in the 2024 race, and label their donations accordingly. Donations in DIME are already linked to FEC data and include information on the recipient's party and type (candidate or committee). To ensure consistency with

[12] While federal contracting data has information on both the subsidiary and parent firm awarded the contract, our decision to focus on parent firms is driven by the higher probability of larger firms making donations and their capacity to protect subsidiary firms.

Figure 2: Firms' Donations and Involvement in Public Procurement.



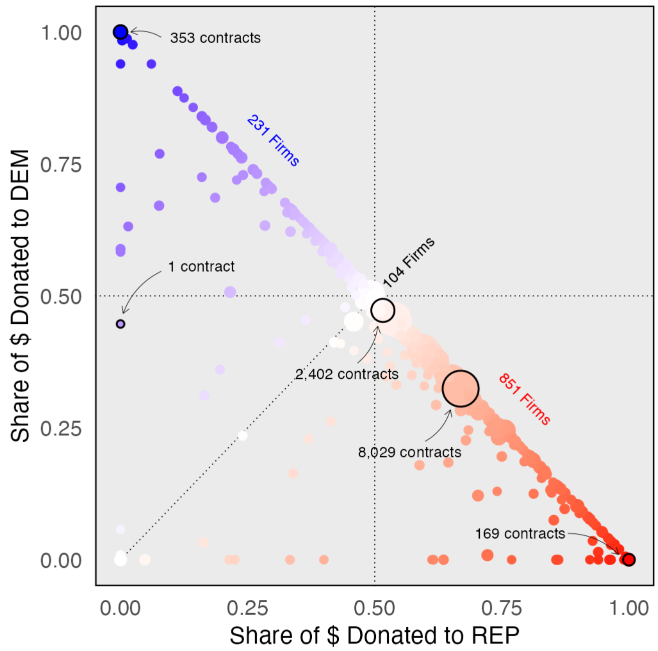
Notes: Number of firms and percentage of donor firms by number of contracts awarded to each firm (left panel) and value of contracts awarded to firms in million dollars (right panel).

OpenSecrets, we restrict donations to those made to federal offices.

By linking campaign contribution records of firms to our sample of active contracts based on the information on firms that won these contracts, we establish two stylized facts about corporate political giving and federal contracting. First, donor firms receive a disproportionately large share of federal contracts—both in terms of the number of awards and total contract value. Although donor firms constitute only 2.1% of all firms in our sample of active contracts, they account for 18% of the total number of contracts and 55% of the total contract value in our sample of active contracts.

Figure 2 illustrates this relationship. The horizontal axis shows the binned number of contracts awarded to each firm (left panel), as well as the total value of contracts awarded (in millions of dollars, right panel). The left vertical axis indicates the number of firms in each bin, while the right vertical axis shows the percentage of firms in each bin that made political contributions. Among the 28,181 firms that were awarded only one contract, just 1% are donors. In contrast, 20% of the 643 firms awarded more than 100 contracts made donations. A similar pattern emerges with contract value: only 1% of firms receiving contracts worth less than $500,000 are donors, while 30% of the 550 firms receiving over $500 million in contracts made political contributions.

Figure 3: Firms' Relative Donations by Number of Contracts Awarded.



Notes: Share of donations made to the Republican (horizontal axis) and Democratic (vertical axis) in the 2024 election cycle. Each point represents a firm. The color of the points indicates the extent to which the firm donates more to either party. The size is a function of the number of contracts awarded to firms.

Second, firms involved in federal contracting do not donate in a bipartisan manner. Figure 3 offers a more detailed view of the partisan distribution of donations by plotting each firm's relative share of contributions to the Republican party (horizontal axis) and the Democratic party (vertical axis). While 75% of donor firms give to both parties, the amounts are often unevenly distributed. Each point represents a firm, with its color indicating the donation gap – firms giving more to Republicans (Democrats) are shaded more intensely red (blue). If firms donated equally to both parties, we would observe many points along the 45-degree diagonal. In practice, only 104 firms donate equal amounts to both parties, whereas 851 firms favor Republicans and 231 favor Democrats.

Research Design

To identify the effect of firms' political contributions on the likelihood of contract termination, the ideal experiment would compare identical contracts awarded by the same federal agency to two otherwise identical firms, differing only in their history of campaign donations. Clearly, making a campaign donation can be highly correlated with the type of services offered by the firm (and hence the type of contracts awarded), and with other, unobservable characteristics of firms.

To mitigate concerns about omitted variable bias, we estimate a stringent regression model that relates the probability of contract termination to firms' campaign contributions restricting the comparison to very similar contracts awarded by the same agency in the same year, while holding constant a wide range of firm and contract characteristics that could support alternative explanations unrelated to firms' political contributions. The unit of observation is, therefore, the individual contract, and the source of identifying variation comes from these narrowly defined groups of contracts being awarded to firms with differing political contribution records.

Specifically, we estimate regressions of the form:

$$y_i = \alpha_{ap} + \delta^T_{at} + \gamma_{d(i)} + \phi_{d(f)} + \beta^P \text{ Donations}^P_f + \zeta' \mathbf{x}_f + \upsilon' \mathbf{z}_i + \epsilon_i \tag{1}$$

where y_i is a dichotomous indicator equal to 1 for terminated contracts and 0 otherwise, α_{ap} are agency $\times$ product/service code fixed effects, which allow us to compare very similar contracts awarded by the same agency.[13] These fixed effects also capture the different baseline probabilities of federal agencies being targeted by DOGE, as determined by factors such as the "ideology" of the agency's mission or its level of insulation from political control (e.g., independent agencies versus bureaus within executive departments). δ^T_{at} captures two time dimensions of contract interacted with agency dummies, namely the year of contract initiation and expected termination. These fixed effects allow for restricting comparisons within sets of contracts awarded by the same agency in the same year, and mitigate the concern that DOGE was targeting contracts signed under the previous Democratic administration. $\gamma_{d(i)}$ are fixed effects for the current congressional district where the contract is performed, and aim at controlling for district-specific characteristics that might be correlated with DOGE's

[13] There are 2,132 product/service codes in our sample, and they are fine-grained enough to distinguish, for example, between "IT AND TELECOM SYSTEMS DEVELOPMENT (D302)" and "IT AND TELECOM DATA ENTRY (D303)". Our results are robust if we instead include agency $\times$ industry code (NAICS code) fixed effects, as well as using the triple interaction of agency $\times$ product/service code $\times$ industry code (see Table G.10).

contract terminations (e.g., DOGE might be less likely to terminate contracts performed in red districts or states). We also include fixed effects for the current congressional districts of the recipient firm ($\phi_{d(f)}$), thus excluding alternative explanations centered on the party controlling the district and the favors a firm can obtain from their representative.[14]

β^P are our key parameters of interest, capturing the change in the probability of contract termination for recipient firms resulting from a one-unit increase in the total amount of donations to the Republican or Democratic parties, as well as other non-partisan donations. Note that for non-donor firms, Donations equal 0 for every $p \in \{\text{Dem, Rep, Other}\}$.[15] To ease interpretation, we scale the donation amounts so that a one-unit increase equals $+\$100,000$, which is approximately $1/3$ of a standard deviation for donations to Republicans, $1/2$ of a standard deviation for donations to Democrats, and 5 times the standard deviation for donations to other parties.[16]

We also include a set of firm-specific covariates ($\mathbf{x}_f$), which allow us to hold fixed other characteristics of the firms that might be correlated with donation behavior and the probability of contract termination (e.g., small businesses or firms owned by women might be more likely to supply contracts more heavily targeted by DOGE). In particular, we include eight dichotomous covariates capturing the firm's ownership—whether the firm is owned by a foreign entity, women, veterans, or ethnic minorities—, whether the firm is a non-profit organization, considered small or big businesses by the awarding agency, participates in a program designated for disadvantaged firms, and is located in a historically underutilized business zone. Moreover, we control for firms' total number of contract awards and total contract amounts based on contracts awarded between fiscal years 2004 and 2024 and terminated prior to January 20, 2025, as a way of measuring the extent to which firms have been dominant in federal contracting.

To ensure we are comparing contracts of similar value, topic and objective measures of

[14] 42% of our contracts are performed in districts different from where the firm is located.

[15] In the Appendix, we also estimate Equation 1 on donor firms alone and we find even larger effects of firms' donation amounts (see Table G.15).

[16] When including firms that do not donate, the average donation to Republicans is \$96,000, to Democrats is \$66,000, and to other parties is \$1,415. See Table C.5 in the Appendix for the full distribution of the donation amounts.

inefficiencies, we also include a vector of contract-level covariates ($\mathbf{z}_i$), namely whether the description of the contract mentions "buzz" words related to diversity, equity, and inclusion (DEI), environmental justice, and foreign aid. We also include monetary indicators capturing the value of the total potential contract, amounts already obligated and disbursed. Moreover, we capture two efficiency-related measures at the contract level and include them as covariates: contract-level in-scope cost overruns and delays.[17]

Despite the stringent specification, it remains possible that Democratic and Republican donor firms procure systematically different types of contracts from the federal government. This heterogeneity could confound the observed relationship between firms' political giving and DOGE contract termination. For example, the contract "Office of Equal Rights Organizational Health Assessment Support Services", awarded by the Department of Homeland Security under product code "Support - Professional: Other", might be more likely to be terminated than the contract "Technical Support for Response and Recovery Missions", awarded by the same agency under the same product code. We refer to this dimension of contract heterogeneity as a latent potential for termination, given DOGE's mission and motives. To quantify this trait as objectively as possible, we adapt the machine learning approach proposed by Iaria, Schwarz, and Waldinger (2024), which estimates the citation potential of academic papers based on their title. In a similar spirit, we extract text features from the contract description and use them to train a machine learning classifier that predicts the likelihood of contract termination. To avoid bias stemming from campaign contributions, the model is trained exclusively on contracts awarded to non-donor firms. The steps are described in detail in Section E of the Appendix. With the classifier, we estimate the predicted probability of termination for all contracts in our sample and include this as a contract-level control in $\mathbf{z}_i$.

We cluster the standard errors for the error term ϵ_i at the parent firm level, corresponding to the level of treatment assignment.

[17] We measure cost overrun for contract i as $(\text{ex-post realized cost}_i - \text{initially expected cost}_i)/\text{initially expected cost}_i$. Similarly, contract-level delay for contract i is calculated as $(\text{ex-post completion time}_i - \text{initial completion time}_i)/\text{initial completion time}_i$. We convert both measures into binary indicators, coded as 1 if there is an in-scope cost overrun or delay, and 0 otherwise.

Results

We present three sets of results. First, we estimate the average effect of firms' donations on the probability of contract termination, plausibly holding all else equal. Second, we examine heterogeneity in these effects by state and district partisanship, as well as by the ideological leaning of the contracting agency. Third, we exploit the timing of the Wisconsin Supreme Court election, showing how this high-stakes race temporarily prevented DOGE from targeting firms based in Wisconsin until the election date.

DOGE Targets Democratic Donors and Spares Republican Donors

Our main results are reported in Table 1, where we present the estimates for β^P, starting with a parsimonious specification that includes only agency-product fixed effects (Column 1), and progressively adding fixed effects up to our most stringent specification as shown in Equation 1 (Column 4). The dependent variable, whether the contract has ever been terminated by DOGE, is multiplied by 100; hence, estimates represent percentage point changes in the probability of termination.

The results broadly indicate that firms' donations to the Republican and Democratic parties have opposing effects on DOGE's contract cancellation activities. Contracts are less likely to be terminated by DOGE if the firms awarded those contracts donated more to the Republican party in the 2024 election, and the opposite effect occurs if firms donated more to the Democratic party. The point estimates are small in absolute terms, but sizable if compared to the baseline probability of contract termination (1.4%). In the most stringent specification of Column 4, donating $+\$100,000$ to the Republican party decreases the probability of contract termination by 0.22 p.p., a 15% decrease compared to the average probability of termination, whereas a same-size increase in donations to the Democratic party increases the probability of termination by 0.35 p.p., equal to 25% of the mean.

Consistent with our argument of political targeting, the estimates for donations to other parties are approximately 0 and very noisy. These findings suggest that DOGE considered the

Table 1: Firms' Political Giving and DOGE Contract Termination.

	Contract Terminated (× 100)			
	(1)	(2)	(3)	(4)
$ Donated to Republicans	-0.14	-0.14*	-0.22**	-0.22**
	(0.08)	(0.08)	(0.10)	(0.09)
$ Donated to Democrats	0.21*	0.23*	0.35**	0.36**
	(0.13)	(0.12)	(0.16)	(0.16)
$ Donated to Other/Non-Partisan	-0.01	-0.02	0.03	0.01
	(0.17)	(0.17)	(0.20)	(0.20)
Firm Covariates	✓	✓	✓	✓
Contract Covariates	✓	✓	✓	✓
R^2	0.32	0.33	0.33	0.33
Observations	545,382	545,382	544,165	544,165
Mean DV (% Terminated Contracts)	1.43	1.43	1.42	1.42
Agency-Product FE	✓	✓	✓	✓
Agency-Year End of Contract FE		✓		✓
Agency-Year Start of Contract FE		✓		✓
Congressional District (Firms) FE			✓	✓
Congressional District (Contract) FE			✓	✓

Notes: OLS estimates. Standard errors, clustered at the recipient parent firm level, are reported in parentheses. The dependent variable is a binary indicator equal to 100 if the contract was terminated by DOGE, and 0 otherwise. Donation amounts to Republicans, Democrats, and Other/Non-Partisan groups are measured in $100,000s. Signif. codes: ***: 0.01, **: 0.05, *: 0.10.

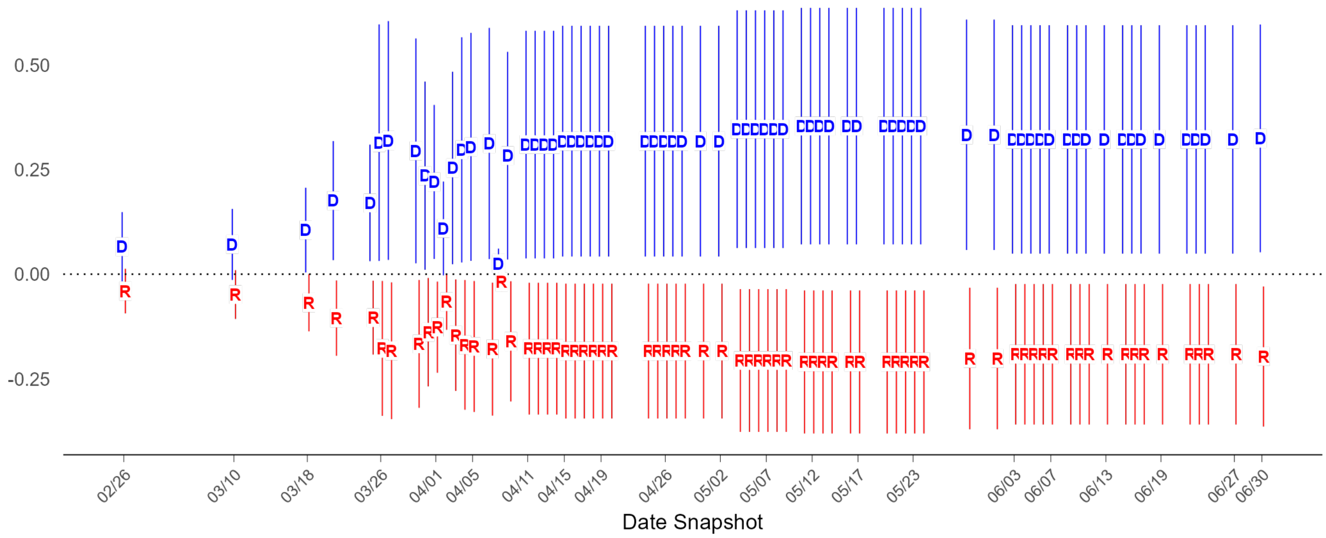
extent to which firms signaled loyalty to the Republican party by donating relatively more.[18]

The richness of our data also allows us to examine dynamic effects by estimating the impact of firms' contributions across the 71 snapshots of data collection. Recall that the outcome variable used in Table 1 indicates whether a contract has *ever* appeared as terminated on the DOGE website across all snapshots. Given the speed at which DOGE operations unraveled, one might expect that targeting took time to manifest in the data, and that the estimates presented in Table 1 are primarily driven by the most recent snapshots. However, our results suggest that DOGE was highly effective at rapidly targeting contracts based on the awarded firm's campaign contribution records—as early as March 21, 2025.

These results are shown in Figure 4. The horizontal axis displays the various snapshots of

[18]The full sets of covariate coefficients are reported in Table G.12 in the Appendix. As expected, the covariates with the strongest associations with the probability of contract termination are "DEI Contract", "Environmental Justice Contract", and the predicted probability of termination.

Figure 4: Firms' Political Giving and DOGE Contract Termination Across Snapshots.



Notes: OLS estimates and 95% confidence intervals. Standard errors are clustered at the recipient parent firm level. The dependent variable is a binary indicator equal to 100 if the contract was terminated by DOGE, and 0 otherwise, in any given snapshot of data collection (reported on the horizontal axis). Donation amounts to Republicans and Democrats are measured in $100,000s.

data collection, from February 26 to June 30, 2025, while the vertical axis reports the estimated effects of donations to the Democratic party (in blue) and Republican party (in red). Each pair of coefficients is estimated using the same dataset of active contracts employed in the previous analysis, with the only difference being that contracts are marked as terminated if they appear on DOGE's *Wall of Receipts* on the date of the snapshot.

The figure suggests that the effects of firms' campaign contributions have grown stronger over time, although we are able to reject the null hypothesis of no effect of firms' campaign contributions already on our third snapshot on March 18. Even though the estimates are noisier for the earlier snapshots, they still point to the same direction: positive for donations to Democrats and negative for donations to Republicans. These results demonstrate that politicized and unbound government agencies can be highly effective in accommodating the president's political objectives.

In the Appendix, we present additional analyses designed to assess the robustness of our results. First, it is possible that donor and non-donor firms differ from one another in unobservable ways. To make progress, we demonstrate that the results become even stronger when the analysis is limited to donor firms (see Table G.15). Second, to ensure the results are not driven by extreme values on the independent variables, we winsorize the data sequentially, excluding mega-donor firms donating more than *i)* \$500,000, *ii)* \$ 1 million, *iii)* \$ 1.5 million to either party (Table G.16). We further show the results are robust to alternative specifications of fixed effects (Table G.10), omitting covariates to avoid suppression effects (Table G.12), and excluding contracts awarded by USAID or to firms based in the DC area (Table G.14). Given the specificity of defense contracts and the greater influence of Presidents over foreign affairs (Canes-Wrone, Howell, and Lewis 2008), we find that the results are even larger when excluding contracts awarded by the Department of Defense (Figure G.4). Finally, the effects of firms' contributions become larger if we subset the data to large contracts and large firms with more than 100 awarded contracts (Table G.13).

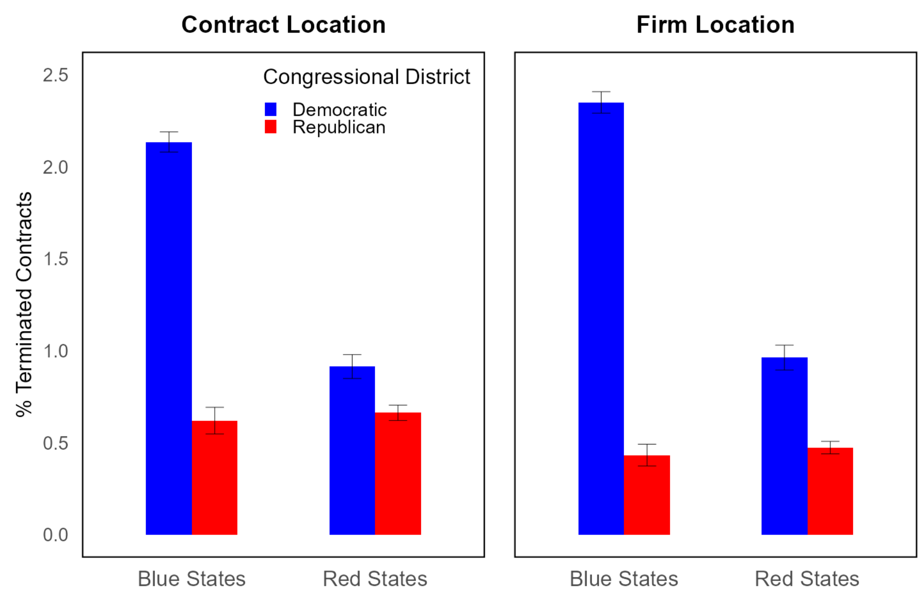
We further assess the robustness of our findings against several alternative explanations in Appendix H. We find that our results are unlikely to be driven by factors such as: DOGE selectively disclosing politically motivated contract cancellations; DOGE targeting contracts awarded to Democratic donor firms that newly entered federal contracting during the Biden administration; DOGE mechanically canceling contracts disproportionately awarded to Democratic donor firms; or firms making campaign contributions endogenously in response to the political landscape of their location.

DOGE's Targeting Takes Place Only in Less Republican-Favorable Locations

Firms' campaign contribution records may represent only one political dimension driving DOGE's contract termination activities. These patterns may coexist with policy or geographical considerations—for example, a greater intensity of terminations in blue states or among federal agencies with more liberal missions.

To shed light on these heterogeneous effects, we next examine whether the effects of firms' campaign contributions diminish if contracts are performed in or awarded to firms based in districts controlled by the president's co-partisan legislators or in states with a majority of

Figure 5: Baseline Probability of Contract Termination by District and State Partisanship.



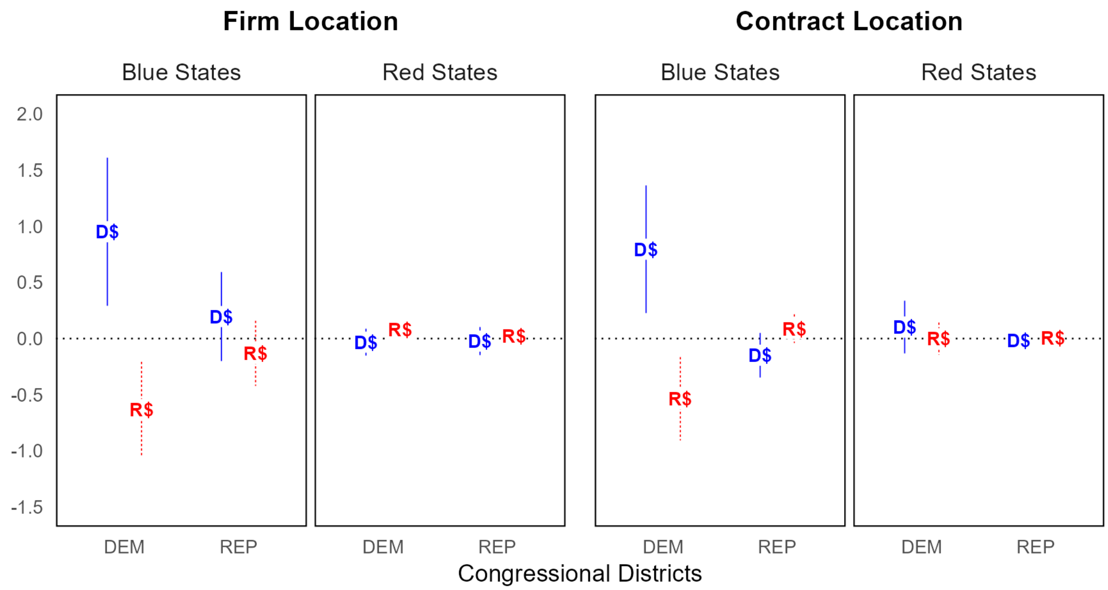
Notes: Percentage of terminated contracts by district and state partisanship. District partisanship is measured by the party of the candidate who won the district, while state partisanship is based on the presidential candidate who received the majority of votes in the state.

like-minded voters. These expectations are motivated by a large literature showing that Presidents often prioritize directing federal spending to areas favorable to them or their party (e.g., Berry, Burden, and Howell 2010; Kriner and Reeves 2015; Dynes and Huber 2015; Christenson, Kriner, and Reeves 2017). If this is the case, DOGE might have spared contracts awarded to such areas, regardless of how much the associated firms donated in the 2024 elections.

For our analysis, we examine heterogeneity by legislator and state partisanship associated with federal contracts. To do so, we split our sample into four based on two criteria: (1) whether the awarded firm is based in blue or red states based on the vote share in the 2024 presidential election, and (2) whether the firm awarded the contract is based in congressional districts represented by Democratic or Republican House representatives. We can also split our sample into four using the information on where the contract is performed.

By relying solely on descriptive evidence, striking differences emerge in the probability of contract termination by legislator and state partisanship. Figure 5 shows the proportion of DOGE-terminated contracts among all active contracts in each subsample. The results indicate that the likelihood of DOGE-initiated contract termination is higher for contracts

Figure 6: Heterogeneity by States' and Districts' Partisanship.



Notes: OLS estimates and 95% confidence intervals. SE clustered by recipient parent firm. Same covariates and specification presented in Equation 1.

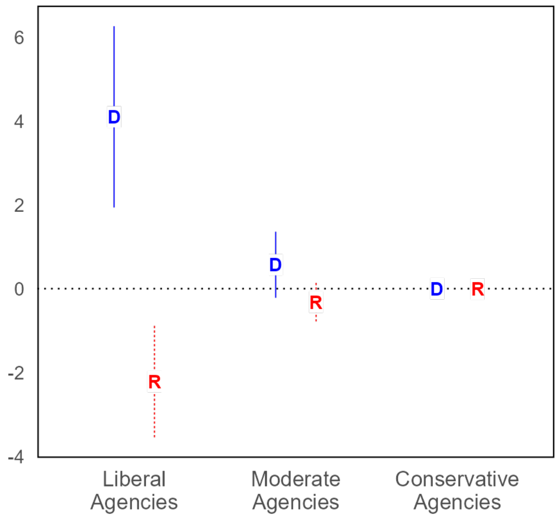
associated with blue states, particularly those in districts represented by Democratic members of the House. These locations are considered the most politically unfavorable to the Trump administration. The findings suggest that DOGE may have been targeting contracts directed toward political opponents, based on both voters' and legislators' partisanship.

For each split sub-sample, we estimate the same regression model as in Equation (1) and present the results visually in Figure 6. Each panel displays the estimated effect of firms' donations to the Republican party (in red) and Democratic party (in blue) across the four combinations of red-blue districts and states, both using information on firms' locations and contract performance to measure contract-level partisanship.

The findings clearly suggest that the positive (negative) effects of firms' donations to the Democratic (Republican) party are primarily driven by contracts associated with the least Republican-leaning locations. These results are consistent whether we measure location based on where the contract is performed or where the firm is based, despite limited overlap between the two—only 58% of contracts are awarded to firms located in the same district where the contract is performed.[19]

[19] As an additional analysis, we divide states into the president's core, swing, and non-core states. Swing

Figure 7: Heterogeneity Analysis by Agencies' Perceived Ideology.



Federal Agencies	N. Awarded Contracts	% Terminated Contracts
Liberal Agencies	52,610	7.99
Moderate Agencies	96,992	1.67
Conservative Agencies	392,245	0.46

Notes: OLS estimates and 95% confidence intervals. SE clustered by recipient parent firm. Same covariates and specification presented in Equation 1.

We now turn to the ideological mission of federal agencies and examine whether the heterogeneous effects we find for legislator and state partisanship replicate when looking at the mission of the agency. To measure agency ideology, we use the estimates produced by Richardson, Clinton, and Lewis (2018), who produce time-fixed estimates of the perceived ideological leaning of agencies' mission by modeling expert survey responses to measure the latent ideological leaning of federal agencies on a liberal-conservative scale. We are able to match 47 out of 71 agencies to the ideology data. Since our fixed effects at the agency-product level do not allow for parametrically estimating the moderating effect of agency ideology, we use the same strategy we adopted for the district/state partisanship heterogeneity analysis and split the agencies in our data into three equal-sized bins based on their ideology score into liberal, moderate, and conservative agencies.[20]

The distribution of contracts by agency ideology is reported in the table accompanying Figure 7. Given the large share of contracts awarded by the Department of Defense—an agency

states are defined based on the 2024 presidential election results as those with a vote margin of less than 10%, and include Arizona, Georgia, Michigan, Nevada, North Carolina, Pennsylvania, and Wisconsin, and do not overlap with core or non-core states. Figure G.5 shows that the effects of firms' donations are small and imprecisely estimated for contracts awarded to firms located in the president's core and swing states. Our findings are consistent with models of distributive politics that argue incumbent parties benefit core supporters (e.g., Cox and McCubbins 1986).

[20]The full list of matched agencies and their ideology estimate is reported in Table F.9 in the Appendix.

with a conservative ideological mission—the majority of contracts (72%) are classified as being awarded by a conservative agency. In contrast, the shares awarded by liberal and moderate agencies are more balanced, accounting for 10% and 18% of contracts, respectively. We find that the probability of contract cancellation is disproportionately higher among contracts awarded by liberal firms, where approximately 8% of contracts have been canceled, compared to the 1.67% of contracts awarded by moderate agencies and, despite the larger number of awards, the 0.5% of contracts awarded by conservative agencies.

We then estimate our main regression model across three sub-samples, including contracts awarded by liberal, moderate, and conservative agencies, and report three pairs of coefficients, one—for firms' donations to the Republican and Democratic party—for each bin of agencies. The results in Table 7 display large heterogeneity in the effect of firms' donation record, which is concentrated among contracts awarded by liberal agencies, where the effects are much larger than those presented in Table 1, even when accounting for the larger baseline probability of contract cancellation. It is worth noting that, given the large sample size for contracts awarded by conservative agencies, we can precisely estimate the effect of firms' contributions to be equal to 0 among this subset of contracts, whereas the effects point to the expected directions but are noisy in the sub-sample of moderate agencies.

Taken together, our heterogeneity analyses suggest that, in deciding which contracts to terminate, DOGE considered not only firms' recent campaign contributions to the Democratic and Republican parties, but also—perhaps even more importantly—the partisanship of voters and legislators associated with those contracts and the ideological mission of awarding federal agencies.

DOGE's Response to The Wisconsin Supreme Court Elections

The election for the Wisconsin Supreme Court justice drew significant attention as the most expensive judicial race in U.S. history, with the potential to either confirm or overturn the sitting liberal majority and affect abortion rights, electoral laws, and redistricting in a key battleground state. Moreover, it was seen by many as a referendum on swing state voters' views of the country's direction during Trump's second term. As a result, out-of-state donors, wealthy individuals, and interest groups poured millions of dollars into supporting one of the two candidates, the Trump-endorsed Republican candidate Brad Schimel or the Democrat-backed candidate Susan Crawford (Bannon 2025).

National figures and organizations showed significant interest in the race. Among them, Elon Musk and political groups tied to him spent more than $21 million to mobilize voters and run advertisements supporting Schimel (Ulmer 2025). Besides donating money, Elon Musk actively campaigned for Schimel, organized rallies, visited the state on the eve of election day, and reported that the race would have "affect[ed] the entire destiny of humanity" (Schleifer 2025). Despite the considerable financial resources and Trump's efforts to mobilize voters, the Republican candidate ultimately lost.

Given the high stakes of the elections for the Republican Party, the Wisconsin judicial race offers a valuable case to provide additional evidence of DOGE's politically motivated contract cancellations. Since canceling contracts can impose significant costs on firms, employees, and constituents who benefit from the services provided through government contracts, it is plausible that DOGE held off on terminating contracts with Wisconsin-based firms in the lead-up to the election—only to increase cancellations in the aftermath. Recall that for each contract *ever* posted as terminated on the DOGE website, we observe the date when the contract was uploaded for the first time. We can therefore compare the share of firms' contracts canceled before and after the Wisconsin April 1st elections for in-state firms and out-of-state firms, in a difference-in-differences design.

1.2% of firms in our sample of active contracts are based in the state, and these firms account for 1.9% of all awarded contracts, roughly in line with the national average by state. However, prior to April 1st, the average number of terminated contracts in other states was 13 times higher than in Wisconsin (95 versus 7). Between April 2nd and the end of June, the average number of terminations in other states declined to 62, while the number of terminated contracts in Wisconsin doubled to 14.

To estimate the impact of the Wisconsin elections on the share of terminated contracts among firms based in Wisconsin, we construct a panel data set at the firm-month level, spanning from February to June 2025.[21] Treatment firms are those based in Wisconsin, whereas control firms are those based in any other state. The post-treatment period begins in April, given that the election day for the Supreme Court seat was held on April 2nd, 2025. For each firm-month observation, we track the share of DOGE-terminated contracts by using the timestamp when DOGE uploaded the contract to its website to determine the month of contract termination.

We then estimate the following difference-in-differences event-study specification:

$$y_{jt} = \alpha_j + \delta_t + \sum_{\tau \neq -1} \beta_\tau \cdot \mathbf{1}[D_j = 1] \cdot \mathbf{1}[t = \tau] + \epsilon_{jt} \tag{2}$$

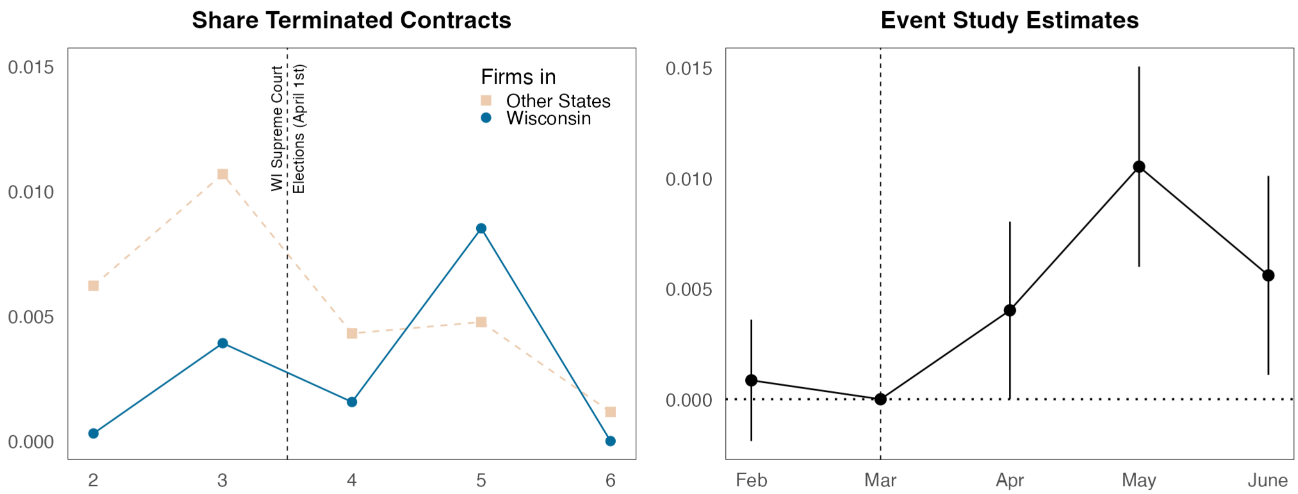
where y_{jt} is the share of terminated contracts for firm j in month t, α_j and δ_t are firm and month fixed effects, respectively. D_j is a treatment indicator equal to one if firm j is based in Wisconsin, τ denotes months relative to treatment. The omitted category is $\tau = -1$ (March), which serves as the reference period. The coefficients β_τ capture the dynamic effect of the Wisconsin Supreme Court election on the outcome for treated firms. Standard errors are clustered at the state level, which corresponds to the level of treatment assignment.

Our main results are presented in Figure 8, which displays, in the left panel, the average share of terminated contracts over time for treated and control firms, and in the right panel, the corresponding event study estimates.

For the estimated effects to be interpreted as unbiased estimates of the average treatment effect of the elections on Wisconsin firms' contract terminations, treated and control firms must have followed parallel trends in the absence of the April 2nd election. Despite the short time series available, both panels provide evidence consistent with this assumption: firms in Wisconsin and in other states exhibited parallel trends during February and March. The divergence begins in April and peaks in May, when the average share of terminated contracts for Wisconsin firms rises sharply, surpassing that of firms in other states. This pattern is

[21] The first date when contracts were posted was January 22nd, 2025, but less than 1% of contracts have been uploaded in January. Therefore, we restrict our search from February to June.

Figure 8: Average Share of Firms' Terminated Contracts and Event Study Estimates.



Notes: Left panel shows the average share of terminated contracts over time for treated and control firms. Right panel reports event-study estimates and 95% confidence intervals of the effect of the Wisconsin Supreme Court Elections on the share of terminated contracts of Wisconsin firms.

mirrored in the event study plot, which shows no difference between treated and control firms in February (relative to the baseline month of March), followed by a positive and statistically significant effect in April. The coefficient peaks in May at approximately +1 percentage point, and declines in June to about half that magnitude, while remaining significantly different from zero at the 95% confidence level.

In Table I.20, we report difference-in-differences estimates limiting the analysis to red states only, blue states and swing states only, and swing states only, and we find similar results to the ones presented in Figure 8.

Examining the Wisconsin Supreme Court election suggests that DOGEs cancellations of contracts awarded to Wisconsin-based firms were more likely in the aftermath of the contentious election.

Discussion

The Department of Government Efficiency represents a major innovation in the way the president controls administrative agencies. Tasked with cutting spending, dismantling regulations, and firing federal bureaucrats, DOGE continues to be a major player in the second Trump administration and a highly divisive force of radical policy change. In this paper, we have used this extraordinary case in contemporary American politics to shed new light on how presidents devise politicized organizations to achieve political goals while defying Congressional oversight and internal bureaucratic resistance.

Combining data on federal procurement, DOGE-terminated contracts, and firms' campaign contributions, we document several patterns in DOGE's activities that may be associated with advancing the president's political goals. Firms donating to the Republican Party were less likely to face contract terminations, while those contributing to Democrats were more exposed—particularly in blue districts within blue states and in agencies with a more liberal ideological leaning. By leveraging the timing of contract terminations and the 2025 Wisconsin Supreme Court election, we show that contract cancellations by DOGE increased for Wisconsin-based firms only after the election concluded, when the risk of electoral backlash had passed.

Together, these findings suggest a rapid and sophisticated operation by DOGE that advanced the president's policy priorities—such as concentrating terminations in liberal-leaning agencies—and electoral objectives, by shielding Republican-aligned firms and targeting Democratic donors. The Wisconsin case highlights the temporal dimension of this strategy, suggesting that DOGE might have timed its actions to avoid disrupting a politically sensitive election.

Given its ongoing evolution, this paper offers an initial attempt to document how President Trump is using DOGE as a vehicle for policy change—often bypassing established procedures and circumventing Congressional oversight. While public procurement remains one of the largest components of federal spending, DOGE has also been active in reducing the federal workforce, encouraging voluntary employee departures, seeking access to sensitive personal data and payment systems, and developing AI tools aimed at halving the volume of agency regulations (Natanson et al. 2025). These developments open multiple avenues for future research, allowing scholars to explore how DOGE is reshaping presidential policymaking and redefining inter-branch relationships within the U.S. system of separated powers.

While we present evidence on the short-term implications of DOGE's activities, future research should explore the medium- and long-term consequences of its operations for bureaucratic motivation and public trust in government. For instance, Rogowski (2020) finds that the loss of expertise significantly reduces public confidence in the bureaucracy. Layoffs and voluntary departures driven by DOGE are likely to undermine agencies' ability to produce impartial, evidence-based information, thereby weakening the trust that voters and the public place in federal institutions. Moreover, DOGE's mandate to slash the federal workforce may have enduring effects on bureaucratic capacity. As Gailmard and Gailmard (2025, 4) notes, bureaucratic capacity is like an old car: "once turned off, it may require a significant lag to warm back up." The reductions brought about by DOGE's reforms could take years to reverse, with detrimental implications for the quality of services offered and the ability of the federal government to tackle the most pressing policy challenges.

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Appendix

A Sample of Active Contracts . . . A1

B DOGE Terminated Contracts . . . A3

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D Linking Firms with Campaign Contributions Data . . . A8

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A Sample of Active Contracts

Table A.1: Sample Definition for Active Contracts

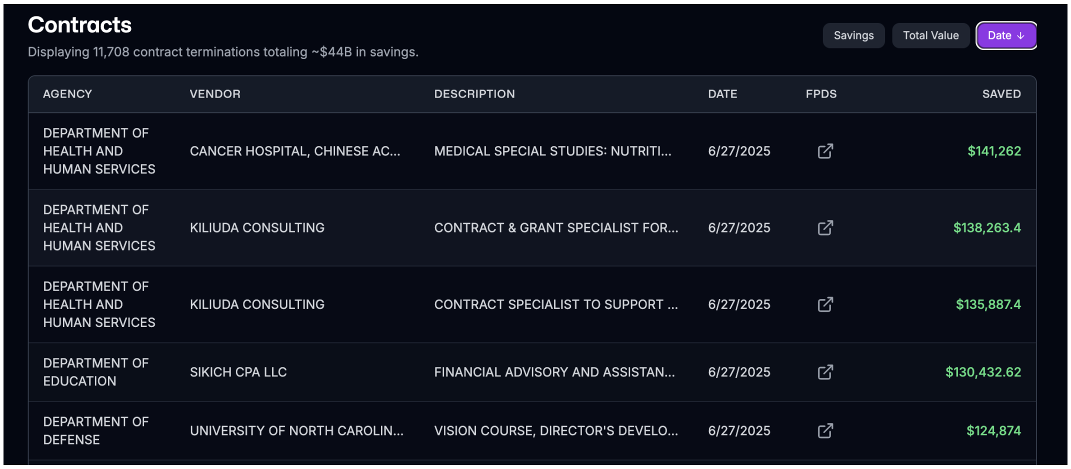
N.	Step	# Contracts
1	Active IDVs + awards as of Jan 20th, 2025	705,035
2	Remove IDVs	580,719
3	Remove contracts awarded to government entitites	572,040
4	Remove contracts performed outside the U.S.	545,459

Table A.2: Number of Active Contracts Signed in Fiscal Year 2004-2025.

Fiscal Year	# Active Contracts
2004	23
2005	48
2006	111
2007	1,029
2008	1,088
2009	374
2010	199
2011	331
2012	178
2013	226
2014	283
2015	800
2016	1,144
2017	1,419
2018	2,296
2019	5,857
2020	17,290
2021	27,283
2022	43,299
2023	69,462
2024	261,869
2025	110,850

B DOGE Terminated Contracts

Figure B.1: DOGE Wall of Receipts.



Contracts

Displaying 11,708 contract terminations totaling ~$44B in savings.

Savings | Total Value | Date ↓

AGENCY	VENDOR	DESCRIPTION	DATE	FPDS	SAVED
DEPARTMENT OF HEALTH AND HUMAN SERVICES	CANCER HOSPITAL, CHINESE AC...	MEDICAL SPECIAL STUDIES: NUTRITI...	6/27/2025		$141,262
DEPARTMENT OF HEALTH AND HUMAN SERVICES	KILIUDA CONSULTING	CONTRACT & GRANT SPECIALIST FOR...	6/27/2025		$138,263.4
DEPARTMENT OF HEALTH AND HUMAN SERVICES	KILIUDA CONSULTING	CONTRACT SPECIALIST TO SUPPORT ...	6/27/2025		$135,887.4
DEPARTMENT OF EDUCATION	SIKICH CPA LLC	FINANCIAL ADVISORY AND ASSISTAN...	6/27/2025		$130,432.62
DEPARTMENT OF DEFENSE	UNIVERSITY OF NORTH CAROLIN...	VISION COURSE, DIRECTOR'S DEVELO...	6/27/2025		$124,874

Notes: Screenshot of DOGE's *Wall of Receipts* with information on awarding agency, vendor, award description, date posted on the website, FPDS link, and estimated amount saved.

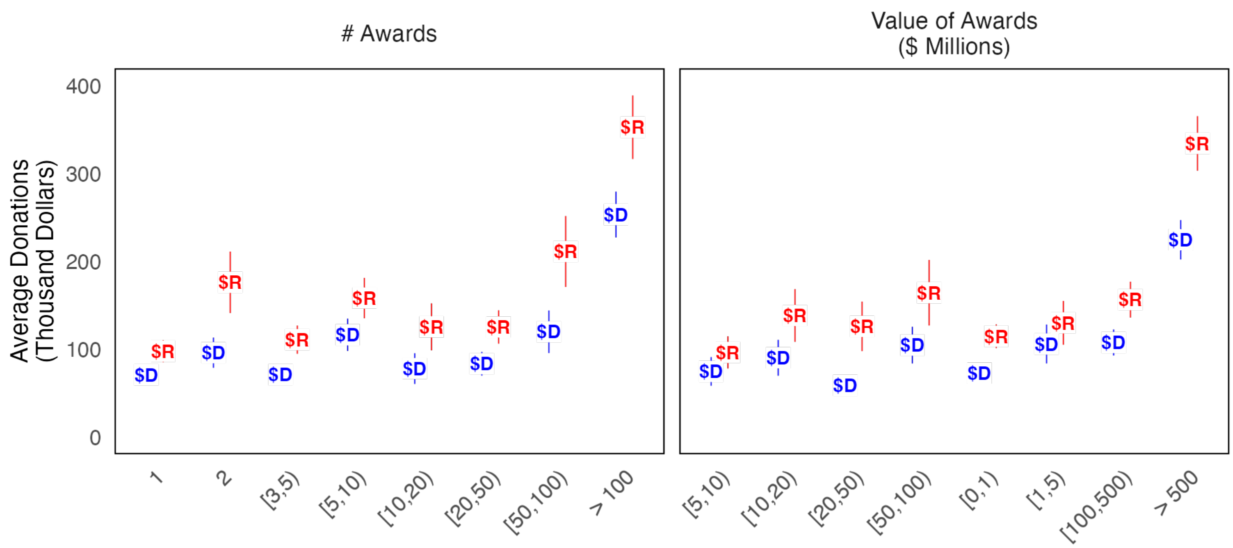
Table B.3: DOGE Contract Removal: Difference in Contract and Firm Characteristics.

	Terminated Contracts				
	Removed		Never Removed		
Variable	Mean	SD	Mean	SD	Difference
Awarded Firm Characteristic					
Foreign Owned	0.032	0.175	0.036	0.186	−0.004
Women Owned	0.225	0.418	0.211	0.408	0.014
Veteran Owned	0.104	0.306	0.118	0.322	−0.013*
Minority Owned	0.214	0.410	0.253	0.435	−0.04*
Non-profit	0.068	0.253	0.080	0.271	−0.011*
Small Business	0.475	0.499	0.558	0.497	−0.083*
C8A Participant	0.149	0.356	0.166	0.372	−0.017*
Historically Underutilized	0.046	0.209	0.056	0.231	−0.011*
Contract Characteristic					
Amount Obligated (Million $)	5.547	39.334	3.159	30.202	2.389*
Tot. Potential Value (Million $)	42.082	370.918	6.799	68.434	35.283*
Total Outlayed (Million $)	3.365	29.235	1.804	22.605	1.56*
DEI Contract	0.031	0.172	0.016	0.125	0.015*
Environmental Justice Contract	0.014	0.117	0.011	0.104	0.003
Foreign Aid Contract	0.087	0.282	0.002	0.047	0.085*

Notes: Difference in means for various firm and contract characteristics between terminated contracts that are removed at least once from the DOGE website across different snapshots and contracts that are never removed.

C Donor Firms and Procurement: Summary Statistics

Figure C.2: Average Donations by Firms' Involvement in Procurement.



Notes: Average firm contributions to the Democratic and Republican parties based on the number of contracts awarded (left panel) and the total value of awards (right panel).

Table C.4: Firms' Involvement in Procurement and Donations to the Republican party.

	DV: Share $ Donated to REP > DEM		
	(1)	(2)	(3)
N. Contracts (log)	0.05^{***}		
	(0.01)		
Avg. Value of Contracts (log $)		0.02^{***}	
		(0.00)	
Total Value of Contracts (log $)			0.02^{***}
			(0.00)
Mean DV	72	72	72
R^2	0.04	0.02	0.04
Observations	1,183	1,183	1,183

Notes: Linear probability estimates with robust SE in parentheses. Binary outcome (whether the firm donates more to the Republican party) related to the number of contracts awarded to the firm (Column 1), the average value of the contract(s) awarded to the firm (Column 2) and the total value of awarded contract(s) (Column 3). Mean DV represents the percentage of firms that donate more to the Republican party.

Table C.5: Distribution of Firms' Donation Amounts.

	Firms' Donations (N = 55,502)				
Party	Min	Median	Mean	Max	SD
Republican	0	0	96,225	2,515,000	303,386
Democratic	0	0	66,287	2,026,750	205,751
Other/Non-Partisan	0	0	1,415	1,250,000	12,226

Notes: Descriptive statistics of firms' contributions to the Republican, Democratic, and Other parties.

D Linking Firms with Campaign Contributions Data

D1 Linking Parent Firms to OpenSecrets

Federal contract data provide information about recipient and parent firm names. OpenSecrets supplies information on PACs' company names and their ultimate organizations (i.e., parent companies). OpenSecrets includes data on 59,515 company name-to-PAC pairs covering the 2012-2022 election cycles. After excluding miscellaneous committees, unions, and ideological PACs, we are left with 23,699 company name-to-PAC pairs. To ensure we are not missing *i*) new firm PACs established in 2024 or *ii*) firm PACs that changed their denomination in 2024 (and not yet included in OpenSecrets 2012-2022 bulk data), we additionally downloaded the list of committees for the 2024 cycle from the FEC website and added 31 such pairs that were not previously included.

Based on the list of (parent) firm names from our sample of active contracts (before any of the sample restrictions described in Table A.1) and the list of company name (ultimate organization)-to-PAC pairs in OpenSecrets, we proceed with the following sequence of name-matching procedures, as shown in Table D.6. Note that once the first procedure is completed and correct matches are identified, we proceed to the second procedure using the list of parent firms that were not matched initially. For the remaining parent firms that are still unmatched after the first and second procedures, we attempt to link their recipient firm names with PAC company names, as shown in row 3 of Table D.6. Once correct matches are identified, we recover the corresponding recipient parent firm.

For fuzzy name matching, we use `fedmatch` package in R, using Jaro-Winkler distance with threshold 0.2. After each name matching procedure described in Table D.6, we check the quality of the matches with the assistance of large language models. The algorithm assigns a similarity score to each match that ranges between 0 and 1. We pass each pair of (parent) recipient firm name-(parent) PAC name matches to Open AI's API, asking the model to decide whether the two strings indeed refer to the same entity. After confirming on a random sample of 100 matches that `gpt-4o` returns the same answer as `gpt-4o-mini` 96% of the time, we decide to use the latter given the higher speed and lower cost. We passed to the API this prompt:

> *You will be given two firm names. Your task is to determine whether they refer to the same entity.*
>
> - *Consider variations like abbreviations (e.g., 'Tech Corp.' vs. 'Tech Corporation') as referring to the same firm.*
> - *If the names clearly represent different entities (e.g., 'JP Morgan' vs. 'Morgan Associates LLC'), treat them as different.*
> - *If one of the names is an acronym and there isn't enough information to confidently link it to the full name, assume they do *not* refer to the same firm.*
>
> *Respond with 'Yes' if the two names refer to the same entity. Respond with 'No' if they do not.*
>
> *Firm name 1: firm_name*
>
> *Firm name 2: firm_name*

We also manually check whether GPT correctly classified (parent) recipient firm-(parent) PAC matches. We finally keep only matches confirmed both by Open AI's model and manual checks.

Table D.6: Order of Name Matching Procedures Using OpenSecrets

No.	Name Matching Procedures
1	Parent Firm Name (Federal Contract) + Ultimate Organization (OpenSecrets)
2	Parent Firm Name (Federal Contract) + PAC Company Name (OpenSecrets)
3	Recipient Name (Federal Contract) + PAC Company Name (OpenSecrets)

As a result, out of 88,745 unique parent firms in our sample including IDVs, we match 1,167 firms with their PACs. Out of 55,202 unique parent firms from our sample imposing sample restrictions, we match 940 firms with their PACs.

D2 Linking Parent Firms to DIME

We perform a similar matching procedure using the Database on Ideology, Money in Politics, and Elections (v 4.0) (Bonica 2024), which includes lists of contributors and recipients from the 1980-2024 election cycle.

From the list of contributors in DIME, we first remove individuals and keep only committees (from 44,905,361 to 3,336,223 contributors). Second, because DIME contains several duplicate records for the same firm (e.g., "amazon com" has seven different identifiers due to the different states in which donations were recorded), we pre-process the text of the name—remove extra spaces, punctuations, and digits—and group all contributors by their pre-processed name and collapse the identifiers. This means that "amazon com" will now have one single entry, with seven collapsed identifiers. After this step, we obtain a list of 2,717,265 contributors with unique names ("amazon com" now has one single row).

Second, we load the list of 88,745 parent firms from our sample of active contracts (before any of the sample restrictions described in Table A.1) and apply the same pre-processing steps to the firm's name.

Third, to match firms in contract data with DIME contributors, we use a deep learning model for record linkage (Arora and Dell 2023) and we perform two symmetric matching steps. First, we assign to each contributor in DIME the best-matching parent firm. For example, DIME contributors "amazon services" and "amazon web services" are both matched with the parent firm "amazon web services inc". Second, we reverse the order and assign to each parent firm in the contract data the best-matching contributor in DIME. In most cases, this step does not result in new matches, but for a sizable group of firms, it adds new matched contributors. For example, consider the parent firm in contract data "johnson controls inc", "johnson controls spa", and "johnson controls industries". These three denominations are, in fact, different names used by the same firm, Johnson Controls. When we perform the first matching between DIME (left) $\rightarrow$ contract data (right), DIME contributor "johnson controls" is matched with contract data parent firm "johnson controls inc". Then, in the second step, when we match contract data (left) $\rightarrow$ DIME (right) each one of the three names of the parent firm Johnson Controls is matched to DIME contributor "johnson control".

These two matching steps return 2,765,664 unique combinations of DIME contributor and parent firm from contract data, each with a similarity score generated by the `linktransformer` algorithm. We subset the 57,218 with a score greater than 0.95 to ensure we select reliable matches.

Fourth, we check the quality of the 57,218 matches with the assistance of large language models as described in the section above. We finally keep only matches confirmed by OpenAI's model. GPT marks 22,157 correct matches, for a total of 12,844 unique parent firms matched to 21,864 unique contributors in DIME. Table D.7 shows an excerpt of the final output of the matching process for the firm Raytheon.

Table D.7: Caption

Firm Name			
DIME Contributor	Contract Data	Score	Collapsed DIME IDs
raytheon	raytheon company	0.99	'2175' '97568' '100046701' '100049499' '100068226' '100137685' '100157050' '100186585' '100186588' '100186589' '100239613' '100239614' '100363776' '100363778' '100527612' '100527613' '100527617' '100527618' '100527619' '101125215' '101125216' '101125229' '101125231' '101125233' '101125246' '101125255' '101125256' '101125257' '101125258' '101125259' '101125261' '104525480' '37642695609' '37648908388' '37648908390' '37649028172' '37649028174' '37649028180' '37649479263' '37649479277' '37649479279' '37649479287'
raytheon co	raytheon company	0.99	'100208856'
raytheon company	raytheon company	1.00	'100208857' '100527611' '101125244' '108153762'
raytheon corporation	raytheon company	0.99	'108175801'

After removing firms already matched on OpenSecrets, we end up with 11,987 contract firms matched to 18,215 DIME contributors.

Because DIME covers election cycles from 1980 to 2024, it is possible that only a subset of these firms made donations in the most recent 2023-24 cycle.

The fifth step consists of using the DIME identifiers of matched firms to extract individual donations. We access the 2023-24 transaction date from DIME, and we subset all donations made by one of the identifiers of matched contributors to federal candidates or committees. We retrieve 5,321 donations made by 337 firms not already matched to OpenSecrets.

Finally, when performing the sample restrictions described in Table A.1, we obtain 243 matched donor firms.

Table D.8 shows the number of donations and the amounts donated by party of the recipient, for firms matched on OpenSecrets and DIME, respectively.

Table D.8: Descriptive Statistics of Campaign Donations of Matched Firms By Source of Data.

	OpenSecrets		**DIME**	
Recipient Party	# Donations	Million $	# Donations	Million $
Republican Party	74,367	168.69	1,820	16.59
Democratic Party	56,205	111.03	2,146	12.76
Other/Non-Partisan	1,290	2.09	888	11.92

Notes: Number of donations and amount donated (in million dollars) by recipient party for firms matched on OpenSecrets and DIME separately.

E Estimating Contracts' Predicted Termination

To estimate the predicted probability of contract termination given the text of the transaction description, we perform the following steps:

1) pre-process contract descriptions;

2) construct a contract-feature matrix X with unigrams and bigrams, where x_{cj} denotes the frequency of feature j in contract c;

3) apply tf-idf reweighting to adjust feature importance;

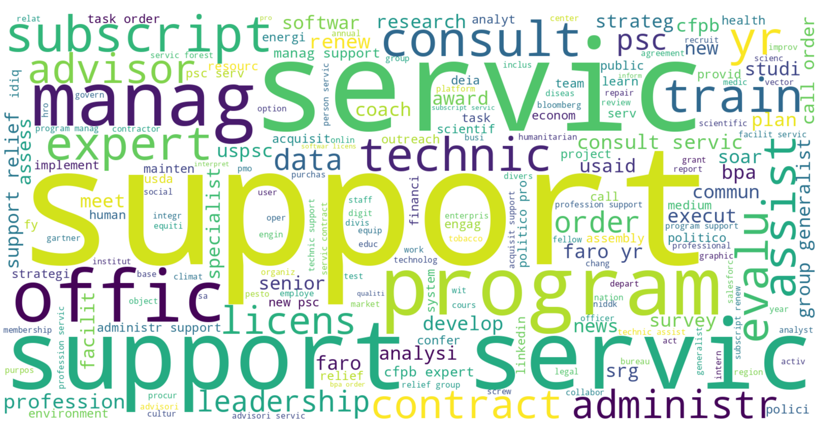
4) train and validate a random forest classifier on contracts awarded to non-donor firms, using the weighted text features to predict whether a contract was ever terminated; and

5) compute the predicted termination probability for each contract, which we include in our set of contract covariates $\mathbf{z}_i$.

Training is limited to contracts awarded to non-donor firms to avoid bias from campaign contributions. To handle class imbalance, we use all terminated contracts and a random sample of non-terminated contracts twice as large. We achieve satisfactory performance metrics, with accuracy on a held-out test set of 0.83 and F1 0.72.

Figure E.3 shows the most important words in predicting contract termination. “Service" and “support" are among the most important text features, which also comprise words such as “leadership", “expert", “train", and “consult". Out of 838,732 unique words used as predictors, “climat" ranks 82nd in terms of importance, and “environment" 116th.

Figure E.3: Most Important Text Features in Predicting Contract Termination.



Notes: The word cloud reports uni-grams and bi-grams that most strongly predict contract termination. The n-grams are identified with a random forest classifier that uses unigrams and bigrams of the description of the contract as inputs.

F Agency Ideology

Table F.9: List of Agencies with Matched Ideology Estimate.

Agency	Ideology Estimate	Ideology Bin
Consumer Financial Protection Bureau	-1.94	Liberal
Peace Corps	-1.80	Liberal
Agency for International Development	-1.59	Liberal
Department of Health and Human Services	-1.57	Liberal
Environmental Protection Agency	-1.51	Liberal
Equal Employment Opportunity Commission	-1.50	Liberal
Department of Education	-1.44	Liberal
Consumer Product Safety Commission	-1.19	Liberal
Department of Labor	-1.17	Liberal
Federal Labor Relations Authority	-1.15	Liberal
National Labor Relations Board	-1.14	Liberal
Merit Systems Protection Board	-1.03	Liberal
Federal Mediation and Conciliation Service	-1.01	Liberal
Corporation for National and Community Service	-1.00	Liberal
Department of Housing and Urban Development	-0.95	Liberal
Department of the Interior	-0.82	Liberal
Department of State	-0.72	Moderate
National Science Foundation	-0.69	Moderate
Federal Housing Finance Agency	-0.67	Moderate
Administrative Conference of the U.S.	-0.62	Moderate
Social Security Administration	-0.54	Moderate
Federal Trade Commission	-0.43	Moderate
Millennium Challenge Corporation	-0.34	Moderate
Department of Justice	-0.34	Moderate
Office of Personnel Management	-0.32	Moderate
Department of Energy	-0.24	Moderate
Department of Transportation	-0.14	Moderate
Department of Commerce	-0.13	Moderate
Federal Election Commission	-0.12	Moderate
National Archives and Records Administration	-0.11	Moderate
National Transportation Safety Board	-0.11	Moderate
General Services Administration	-0.04	Moderate
Federal Communications Commission	-0.03	Conservative
Small Business Administration	-0.03	Conservative
Federal Maritime Commission	-0.01	Conservative
National Aeronautics and Space Administration	0.05	Conservative
Export-Import Bank of the United States	0.10	Conservative
International Trade Commission	0.18	Conservative
Department of Agriculture	0.25	Conservative
Nuclear Regulatory Commission	0.34	Conservative
Commodity Futures Trading Commission	0.60	Conservative
Department of the Treasury	0.64	Conservative
Department of Veterans Affairs	0.67	Conservative
Securities and Exchange Commission	0.73	Conservative
Department of Homeland Security	0.93	Conservative
Overseas Private Investment Corporation	1.05	Conservative
Department of Defense	1.88	Conservative

G Robustness Tests

Table G.10: DOGE Contract Termination: Alternative Fixed Effects Specification.

	Contract Terminated (× 100)		
	(1)	(2)	(3)
$ Donated to Republicans	-0.22**	-0.19**	-0.15*
	(0.09)	(0.08)	(0.08)
$ Donated to Democrats	0.36**	0.35**	0.27*
	(0.16)	(0.14)	(0.15)
$ Donated to Other/Non-Partisan	0.01	0.03	0.00
	(0.20)	(0.23)	(0.15)
Firm Covariates	✓	✓	✓
Contract Covariates	✓	✓	✓
R^2	0.33	0.34	0.48
Observations	544,165	544,142	544,140
Mean DV (% Terminated Contracts)	1.42	1.42	1.42
Agency-Product FE	✓		
Agency-Year Start of Contract FE	✓	✓	✓
Agency-Year End of Contract FE	✓	✓	✓
Congressional District (Firms) FE	✓	✓	✓
Congressional District (Contract) FE	✓	✓	✓
Agency-NAICS FE		✓	
Agency-Product-NAICS FE			✓

Notes: OLS estimates. SE clustered by recipient parent firm in parentheses. The outcome variable is a dummy equal to 100 for terminated contract and 0 otherwise. Signif. codes: ***: 0.01, **: 0.05, *: 0.10.

Table G.11: DOGE Contract Termination: Including IDVs.

	Contract Terminated ($\times$ 100)
	(1)
\$ Donated to Republicans	-0.19***
	(0.07)
\$ Donated to Democrats	0.31**
	(0.12)
\$ Donated to Other/Non-Partisan	0.05
	(0.18)
Firm Covariates	✓
Contract Covariates	✓
R^2	0.35
Observations	683,142
Agency-Product FE	✓
Agency-Year Start of Contract FE	✓
Agency-Year End of Contract FE	✓
Congressional District (Firms) FE	✓

Notes: OLS estimates. SE clustered by recipient parent firm in parentheses. The outcome variable is a dummy equal to 100 for terminated contract and 0 otherwise. Signif. codes: ***: 0.01, **: 0.05, *: 0.10.

Table G.12: DOGE Contract Termination: With and Without Covariates.

	Contract Terminated (× 100)		
	(1)	(2)	(3)
$ Donated to Republicans	-0.22**	-0.16**	-0.22**
	(0.10)	(0.08)	(0.09)
$ Donated to Democrats	0.17	0.29**	0.36**
	(0.17)	(0.14)	(0.16)
$ Donated to Other/Non-Partisan	-0.14	-0.10	0.01
	(0.23)	(0.15)	(0.20)
Foreign Owned			0.21
			(0.20)
Women Owned			0.33***
			(0.11)
Veteran Owned			0.14*
			(0.08)
Minority Owned			-0.35***
			(0.12)
Non-profit			-0.95**
			(0.38)
Small Business			-0.03
			(0.09)
C8A Participant			-0.01
			(0.19)
Historically Underutilized			0.21
			(0.15)
Firms' Total N. Contracts (log)			0.01
			(0.02)
Firms' Total Contract Potetential Value (log)			-0.02
			(0.02)
Amount Obligated (log)			0.07***
			(0.02)
Tot. Potential Value (log)			-0.14***
			(0.02)
Total Outlayed (log)			0.00
			(0.01)
DEI Contract			28.43***
			(2.98)
Environmental Justice Contract			14.30***
			(3.07)
Foreign Aid Contract			-2.75
			(2.27)
Predicted Pr. of Termination			17.83***
			(0.69)
In-Scope Cost Overruns			-0.24**
			(0.10)
Delays			-0.04
			(0.08)
R^2	0.00	0.29	0.33
Observations	545,459	544,234	544,165
Mean DV (% Terminated Contracts)	1.43	1.42	1.42
Agency-Product FE		✓	✓
Agency-Year Start of Contract FE		✓	✓
Agency-Year End of Contract FE		✓	✓
Congressional District (Firms) FE		✓	✓
Congressional District (Contract) FE		✓	✓

Notes: OLS estimates. SE clustered by recipient parent firm in parentheses. The outcome variable is a dummy equal to 100 for terminated contract and 0 otherwise. Signif. codes: ***: 0.01, **: 0.05, *: 0.10.

Table G.13: DOGE Contract Termination: Large Contracts and Large Contractors.

	Contract Terminated (× 100)		
Sample:	All Contracts	Large Contracts (Above $250,000)	Large Contractors (> 100 Awards)
	(1)	(2)	(3)
$ Donated to Republicans	-0.22**	-0.39**	-0.29***
	(0.09)	(0.16)	(0.11)
$ Donated to Democrats	0.36**	0.74***	0.55**
	(0.16)	(0.29)	(0.25)
$ Donated to Other/Non-Partisan	0.01	0.04	-5.77
	(0.20)	(0.37)	(6.71)
Firm Covariates	✓	✓	✓
Contract Covariates	✓	✓	✓
R^2	0.33	0.37	0.36
Observations	544,165	155,828	290,769
Mean DV (% Terminated Contracts)	1.42	1.43	1.43
Agency-Product FE	✓	✓	✓
Agency-Year Start of Contract FE	✓	✓	✓
Agency-Year End of Contract FE	✓	✓	✓
Congressional District (Firms) FE	✓	✓	✓
Congressional District (Contract) FE	✓	✓	✓

Notes: OLS estimates. SE clustered by recipient parent firm in parentheses. The outcome variable is a dummy equal to 100 for terminated contract and 0 otherwise. Signif. codes: ***: 0.01, **: 0.05, *: 0.10.

Table G.14: DOGE Contract Termination: Removing District of Columbia and USAID.

	Contract Terminated (× 100)	
Subset:	No District of Columbia	No USAID
	(1)	(2)
$ Donated to Republicans	-0.24**	-0.22**
	(0.10)	(0.09)
$ Donated to Democrats	0.39**	0.36**
	(0.16)	(0.15)
$ Donated to Other/Non-Partisan	0.00	0.01
	(0.21)	(0.19)
Firm Covariates	✓	✓
Contract Covariates	✓	✓
R^2	0.31	0.28
Observations	533,825	542,991
Mean DV (% Terminated Contracts)	1.43	1.43
Agency-Product FE	✓	✓
Agency-Year Start of Contract FE	✓	✓
Agency-Year End of Contract FE	✓	✓
Congressional District (Firms) FE	✓	✓
Congressional District (Contract) FE	✓	✓

Notes: OLS estimates. SE clustered by recipient parent firm in parentheses. The outcome variable is a dummy equal to 100 for terminated contract and 0 otherwise. Signif. codes: ***: 0.01, **: 0.05, *: 0.10.

Table G.15: DOGE Contract Termination: Sample of Donor Firms.

	Contract Terminated ($\times$ 100)			
	(1)	(2)	(3)	(4)
$ Donated to Republicans	-0.09*	-0.08*	-0.29***	-0.26***
	(0.05)	(0.04)	(0.09)	(0.08)
$ Donated to Democrats	0.16*	0.14**	0.50***	0.43***
	(0.08)	(0.07)	(0.16)	(0.14)
$ Donated to Other/Non-Partisan	-0.19	-0.18	0.17	0.18
	(0.13)	(0.13)	(0.21)	(0.19)
Firm Covariates	✓	✓	✓	✓
Contract Covariates	✓	✓	✓	✓
R^2	0.38	0.42	0.40	0.43
Observations	98,680	98,680	98,491	98,491
Mean DV (% Terminated Contracts)	1.43	1.43	1.43	1.43
Agency-Product FE	✓	✓	✓	✓
Agency-Year End of Contract FE		✓		✓
Agency-Year Start of Contract FE		✓		✓
Congressional District (Firms) FE			✓	✓
Congressional District (Contract) FE			✓	✓

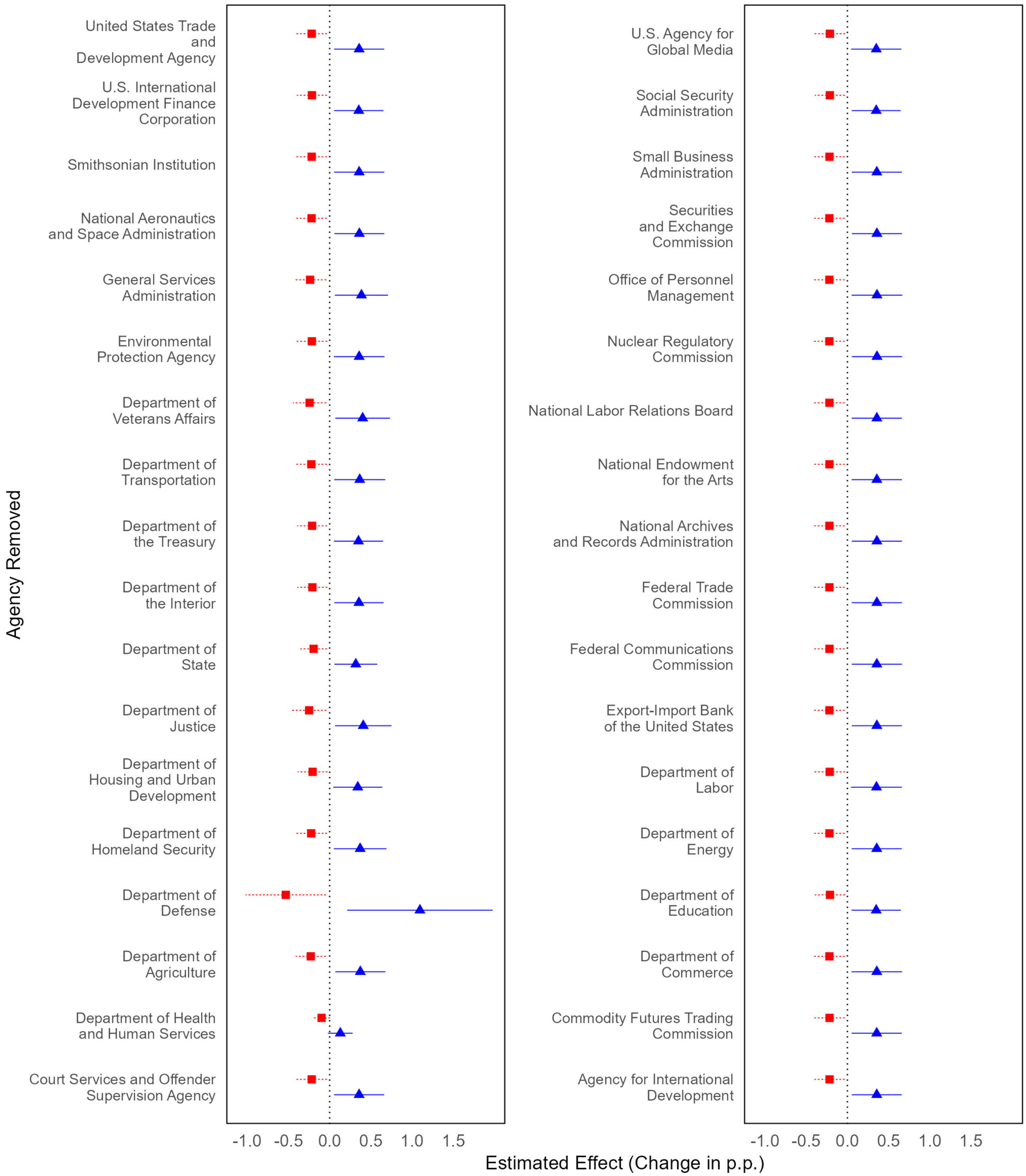
Notes: OLS estimates. SE clustered by recipient parent firm in parentheses. The outcome variable is a dummy equal to 100 for terminated contract and 0 otherwise. Signif. codes: ***: 0.01, **: 0.05, *: 0.10.

Table G.16: DOGE Contract Termination: Winsorizing.

	Contract Terminated (× 100)		
Firms Donating Less Than:	\$ 0.5 Million	\$ 1 Million	\$ 1.5 Million
	(1)	(2)	(3)
\$ Donated to Republicans	-0.43**	-0.58***	-0.40**
	(0.20)	(0.23)	(0.18)
\$ Donated to Democrats	0.74*	0.88**	0.64**
	(0.40)	(0.35)	(0.28)
\$ Donated to Other/Non-Partisan	0.04	-1.11**	-0.55*
	(0.60)	(0.47)	(0.32)
Firm Covariates	✓	✓	✓
Contract Covariates	✓	✓	✓
R^2	0.34	0.34	0.33
Observations	490,812	511,750	522,827
Mean DV (% Terminated Contracts)	1.43	1.42	1.43
Agency-Product FE	✓	✓	✓
Agency-Year Start of Contract FE	✓	✓	✓
Agency-Year End of Contract FE	✓	✓	✓
Congressional District (Firms) FE	✓	✓	✓
Congressional District (Contract) FE	✓	✓	✓

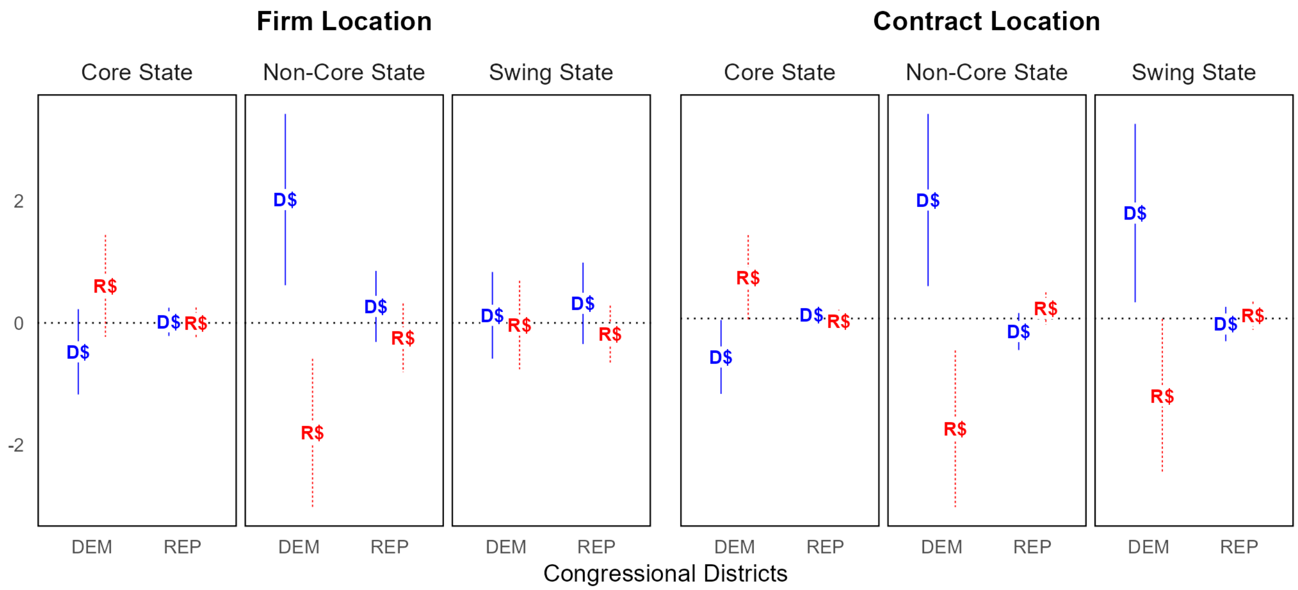
Notes: OLS estimates. SE clustered by recipient parent firm in parentheses. The outcome variable is a dummy equal to 100 for terminated contract and 0 otherwise. Signif. codes: ***: 0.01, **: 0.05, *: 0.10.

Figure G.4: Results Removing One Agency at a Time.



Notes: OLS estimates and 95% confidence intervals across sub-samples of the dataset excluding the agency reported on the vertical axis. The outcome variable is a dummy equal to 100 for terminated contract and 0 otherwise.

Figure G.5: Heterogeneity by States' and Districts' Partisanship.



Notes: OLS estimates and 95% confidence intervals. SE clustered by recipient parent firm. Same covariates and specification presented in Equation 1.

H Addressing Alternative Explanations

First, DOGE claims that they publicly post only about 30% of all contracts, leases, grants that they terminate, raising the possibility that our findings are driven by selective disclosure. That is, even if DOGE terminated contracts awarded to firms that donated to the Republican party at rates similar to those donated to the Democratic party, they may be less likely to publicly post the former on their website. This could reflect a strategic decision to avoid potential backlash from voters or firms aligned with the Republican party. At the very least, Figure 1 shows that the diverging effects on Democratic and Republican donors persist even after DOGE began redacting contract information on its website starting March 25th.

To further address this alternative explanation, we track all contract termination records through June 6, 2025. We then create an alternative outcome variable that equals 1 if a contract was either canceled by DOGE or officially recorded as terminated on the federal contracting database, 0 otherwise. Of all the DOGE-targeted contracts in our sample, 5,559 (77%) are recorded as officially terminated, most commonly under the reason "terminated for convenience." We find that 5,402 contracts were officially terminated but were not explicitly canceled by DOGE.

Using this alternative outcome variable, we re-estimate our main regression model. Table H.17 shows the results. If DOGE did not reveal a substantial number of contracts they officially terminated for the reasons described above, we would expect to observe null results in this model. However, the results in Table H.17 suggest that the effects of firms' donations to Republican and Democratic parties persist.

Second, it may be the case that DOGE was canceling contracts awarded to Democratic donors because many of these firms entered federal contracting for the first time during the previous Biden administration due to their political connections. Since these firms have no prior experience in federal contracting, they may be less efficient, which could justify DOGE's decision to target them.

To address this explanation, we create a binary indicator that equals 1 if a firm had never competed in federal contracting before October 1st, 2020—the beginning of the fiscal year 2021—, otherwise 0. These new entrants account for about six percent of our contract sample, and only 137 Republican donors and 136 Democratic donors fall into this category.

We then interact this binary indicator with the measures of Republican and Democratic donors in the regression model 1. Table H.18 presents the results. The findings suggest that Democratic donors are still more likely to have their contracts terminated, even if they were not new entrants during the Biden administration.

Third, if Republican donors held fewer active contracts at the outset of DOGE's activities, our findings might simply reflect a mechanical effort by DOGE to reduce the disproportionate number of contracts awarded to Democratic donors in order to restore balance. In this case, DOGE's targeting would not necessarily indicate an intentional attempt to penalize political opponents or favor allies. However, as Figure 3 indicates, Republican donor firms were more likely to have received contracts active as of January 20, 2025.

Finally, the null effects for contracts in certain locations may be due to firms' endogenous campaign contributions. That is, if firms expected Trump to win the 2024 election and were located in Republican-favorable areas, they may have refrained from making substantial campaign donations, anticipating that their location alone would secure them political favor. If little corporate donations are made in Republican-favorable locations, the null effects for contracts associated with these locations might be driven by DOGE's inability to use firms'

Table H.17: Firms' Political Giving and Contract Termination Including DOGE Contract Termination.

	Contract Terminated (× 100)	
	(1)	(2)
$ Donated to Republicans	-0.20**	-0.22**
	(0.09)	(0.10)
$ Donated to Democrats	0.36**	0.39**
	(0.15)	(0.15)
$ Donated to Other/Non-Partisan	0.00	0.04
	(0.19)	(0.25)
Firm & Contract Covariates	✓	✓
R^2	0.31	0.28
Observations	544,165	544,165
Mean DV (% Terminated Contracts)	1.42	1.42
Agency-Product FE	✓	✓
Agency-Year Start of Contract FE	✓	✓
Agency-Year End of Contract FE	✓	✓
Congressional District (Firms) FE	✓	✓
Congressional District (Contract) FE	✓	✓

Notes: OLS estimates. Standard errors, clustered at the recipient parent firm level, are reported in parentheses. The dependent variable is a binary indicator equal to 100 if the contract was officially terminated or targeted by DOGE, and 0 otherwise. Donation amounts to Republicans, Democrats, and Other/Non-Partisan groups are measured in $100,000s. Signif. codes: ***: 0.01, **: 0.05, *: 0.10.

campaign donations as a criteria to terminate contracts.

To test this possibility, we compare the within-unit standard deviations of firms' donations to the Republican and Democratic parties based on their locations. If firms' campaign contributions are endogenous in the way described above, we would expect the within-unit standard deviation to be very small in Republican-leaning areas, which could explain the null results. To assess this, we regress firms' donations on the fixed effects from our main regression model and calculate the within-unit standard deviations using the residuals.

Table H.19 shows that the within-unit standard deviation of donations to the Republican party is not smaller in Republican-favorable areas, suggesting that firms in these locations also made substantial contributions to the Republican party. One possible explanation for this lack of endogeneity may be the uncertainty surrounding the 2024 presidential election. As two prominent prediction markets-PredictIt and Polymarket-indicate, the outcome of the 2024 election remained highly uncertain until about one month before election day.[22] Given this uncertainty, firms located in Republican-leaning districts may have been unsure about the level of political protection they would receive based on location alone, prompting them to make campaign contributions in 2024 elections.

[22]See PredictIt (https://www.predictit.org/markets/detail/7456/Who-will-win-the-2024-US-presidential-election) and Polymarket (https://polymarket.com/elections).

Table H.18: Heterogeneity By New Entry After FY 2021.

	Contract Terminated (× 100)
	(1)
New Entrants After FY2021 × $ Donated to Other/Non-Partisan	0.31
	(0.53)
$ Donated to Other/Non-Partisan	0.01
	(0.20)
New Entrants After FY2021	0.19
	(0.13)
$ Donated to Republicans × New Entrants After FY2021	0.22
	(0.95)
New Entrants After FY2021 × $ Donated to Democrats	-0.39
	(1.19)
$ Donated to Republicans	-0.22**
	(0.09)
$ Donated to Democrats	0.36**
	(0.16)
Firm Covariates	✓
Contract Covariates	✓
R^2	0.33
Observations	544,165
Agency-Product FE	✓
Agency-Year Start of Contract FE	✓
Agency-Year End of Contract FE	✓
Congressional District (Firms) FE	✓
Congressional District (Contract) FE	✓

Notes: OLS estimates. SE clustered by recipient parent firm in parentheses. The outcome variable is a dummy equal to 100 for terminated contract and 0 otherwise. Signif. codes: ***: 0.01, **: 0.05, *: 0.10.

Table H.19: Within-Unit Standard Deviations of Firms' Donations to Republican/Democratic Parties

	Republican Donations ($)	Democratic Donations ($)
Republican Districts in Red States	219241.68	144336.89
Democratic Districts in Red States	341436.94	203326.97
Republican Districts in Blue States	141192.67	141192.67
Democratic Districts in Blue States	212919.62	212919.62

I Wisconsin Supreme Court Elections

Table I.20: DOGE Targeting before and after the Wisconsin Supreme Court Elections.

	DV: Share of Terminated Contracts			
States:	All	Red & Swing	Blue & Swing	Swing
	(1)	(2)	(3)	(4)
WI Firm × post	0.006***	0.003***	0.008***	0.004***
	(0.001)	(0.000)	(0.002)	(0.001)
Mean DV (% Terminated Contracts)	0.028	0.013	0.036	0.017
R^2	0.204	0.203	0.204	0.205
Observations	271,225	128,075	182,695	39,545
Firm FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓

Notes: OLS estimates. Standard errors, clustered at the state level, are reported in parentheses. The dependent variable is a binary indicator equal to 100 if the contract was terminated by DOGE, and 0 otherwise. Signif. codes: ***: 0.01, **: 0.05, *: 0.10.