# Does Political Connections Carry Financial Value? Insights from Campaign Donations in Close Elections

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**Abstract**

The debate over whether firms that donate to winning candidates outperform in the stock market due to political influence remains unresolved. The debate is characterized by opposing hypotheses and insufficient causal studies. This study applies a regression discontinuity design (RDD) to close elections in the U.S. to address this question. This study finds no evidence that firms that donate to winning candidates experience better stock market performance. This result remains consistent across various robustness checks, including analyses of political alignment, donation size, time periods, and differences across states.

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# Introduction

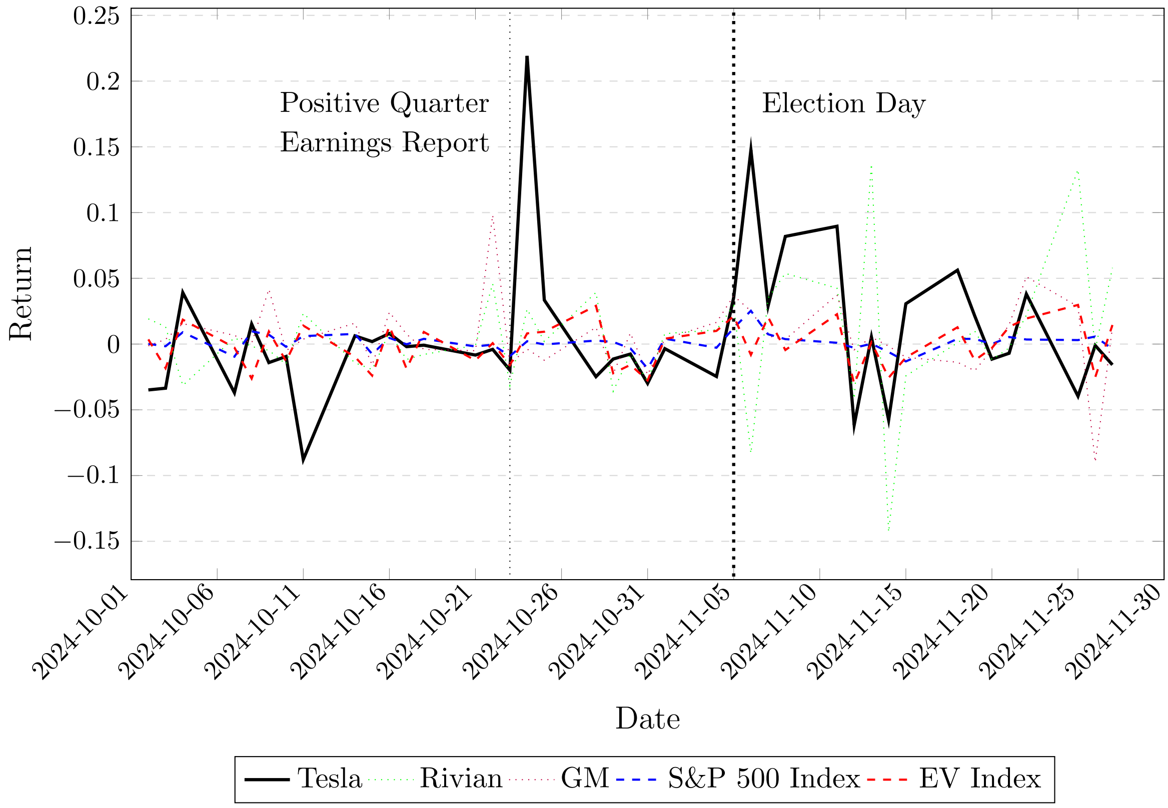
The 2024 U.S. presidential election highlighted a fascinating intersection of corporate influence and political outcomes, with Elon Musk playing a central role. Musk, the CEO of Tesla, emerged as one of the largest donors to Donald Trump's re-election campaign, contributing an estimated $120 million to Super PACs supporting the former president. This substantial financial backing signaled Musk's strategic alignment with Trump's deregulatory policies, especially those affecting the electric vehicle (EV) industry.

Remarkably, as Figure 1 shows, the day following Trump's victory, Tesla's stock soared by 14.8%, significantly outperforming market indices and rival EV manufacturers. Moreover, just two weeks before the election, Tesla shares surged by 22% following strong profit growth. This suggests that the market viewed Trump's victory as a positive factor for Tesla's valuation, similar to the impact of a strong financial quarter.

Analysts suggest this dramatic rise reflected investor optimism about potential regulatory changes under Trump's administration, including reduced subsidies for EVs and heightened tariffs on Chinese competitors, which were seen as benefiting Tesla's dominant position in the U.S. market[1]. This scenario raises critical questions about the link between Musk's campaign donations and Tesla's market valuation. Does every company or businessperson who donates to a winning politician see an increase in their stock value, or was Elon Musk's case an exception? Investigating this relationship provides a unique opportunity to explore the broader implications of corporate political connections on stock performance.

[1] See: Ewing (2024); Palmer (2024); Roush (2024).

Figure 1: Tesla Stock Performance During the 2024 U.S. General Election




**Notes:** The graph illustrates daily returns for Tesla (black), Rivian (green), and General Motors (purple) stocks, alongside the Electric Vehicles Index (red) and the S&P 500 Index (blue), during October and November 2024. Returns are expressed as daily percentage changes in stock prices or index levels and are presented in decimal format. A thin dotted vertical line marks the publication date of Tesla Inc.'s positive quarterly earnings report, while a thick dotted vertical line highlights the 2024 U.S. Election Day (November 5, 2024).

Political connections between firms and politicians are often thought to hold significant financial value for businesses. This study investigates whether firms that contribute to winning political candidates experience measurable financial benefits, focusing on cumulative abnormal returns as an indicator. This study uses a regression discontinuity design (RDD) applied to close elections in the United States, and leverages a rich dataset of political donations, election outcomes, and stock prices from 1980 to 2020 to answer this question. The primary hypothesis posits that firms that donated to winners should observe positive financial effects due to the activation of political connections.

The findings, however, reveal no significant financial benefits for firms associated with winning candidates. Across multiple specifications and robustness checks, the analysis consistently could not find any effect. In the main analysis, I found a small and insignificant effect of 0.1% higher abnormal returns to be associated with winning candidates. These results contrast with those of earlier studies (Cooper et al., 2010; Akey, 2015), which reported a positive relationship between corporate donations and firm returns. By analyzing a more comprehensive and representative dataset, this study provides evidence suggesting that donating to the winning candidate does not universally translate into financial benefits for the donating firms.

The remainder of the paper is organized as follows. Section 2 reviews the related literature, framing the study within the broader discourse on political connections and firm performance. Section 3 outlines the empirical strategy, focusing on the RDD methodology and its implementation. Section 4 details the dataset construction and variables used in the analysis. Section 5 presents the main results, discusses robustness checks and heterogeneity analyses. The last section of this paper concludes with a discussion of the findings, their implications, and suggestions for future research.

# Related Literature

Within political settings, RD is frequently employed to evaluate the influence of election results on various political and economic outcomes.[2] Caughey and Sekhon (2011) have questioned the validity of the electoral RD method due to the incumbent party's tendency to win close elections in the U.S. Congress. However, Eggers et al.

[2]See Lee et al. (2004); Dal Bó et al. (2009); Eggers and Hainmueller (2009); Gerber and Hopkins (2011); Trounstine (2011); Dell (2015); Fiva et al. (2018); Fergusson et al. (2021).

(2015) found no evidence of this issue across different electoral settings, particularly in the context of the U.S. Congress, supporting the general validity of the RD design.

The existing literature has explored the benefits accruing to firms exhibiting a certain level of connectedness to politicians. These inquiries delve into connectedness stemming from (1) direct connections between firms and politicians, such as the inclusion of a politician on the firm's board of directors, and (2) indirect connections such as corporate donations to politicians.

Connectedness arising from direct connections appears to be significant for firm value.[3] However, the impact of indirect connections, particularly those established through donations, on firm returns and value remains inconclusive.

Current research presents two opposing hypotheses. One hypothesis proposes that companies gain "political capital" by making donations, which eventually benefit their shareholders. This hypothesis establishes a causal relationship between political connections formed through donations and the resulting financial gains. The alternative hypothesis suggests that contributing firms may face higher agency costs, i.e. the managers have conflicting interests with those of the shareholders. This leads managers to strengthen their political connections through donations as a safeguard if they need to seek alternative employment. Accordingly, firms making the donations may appear to have decreased value and experience diminished returns, though this is not causally linked to the donations themselves.

In support of the first hypothesis, there are anecdotal evidences suggesting that companies with political connections benefit when those politicians gain power, while firms experience a decline in valuation when they lose such connections due to unexpected events (Roberts, 1990; Jayachandran, 2006; Ferguson and Voth, 2008). Robust

[3] See Fisman (2001); Faccio and Parsley (2009); Faccio (2006); Faccio et al. (2006); Cheng (2018).

analyses found a positive correlation between the number of supported candidates and future abnormal stock returns (Cooper et al., 2010); and even a causal relationship between donating to the winning candidate and stock returns (Akey, 2015). However, the second analysis was limited to a subset of special elections, which constrained its external validity.

In support of the second hypothesis, Aggarwal et al. (2012) found a negative correlation between political donations and future returns. After a case of relaxing constraints on campaign donations by the Supreme Court, Coates IV (2012) found that contributing firms trade at lower Tobin's Q ratios than a control group of firms that do not engage in politics. Fulmer et al. (2023) showed that political donations are associated with reduced civil and criminal sanctions for fraudulent executives.

This paper makes a significant contribution to the field by offering a comprehensive and causally focused analysis of the relationship between corporate political donations and firm performance. Using data spanning all U.S. elections from 1980 to 2020, it significantly extends the temporal and contextual scope of prior studies. By leveraging this expansive dataset, I estimate the effect of donating to the candidate who won on the donating firm's returns. This approach not only provides a more robust understanding of the underlying dynamics but also addresses limitations in the external validity of previous studies.

## Empirical Strategy

In this paper, I will not try to assess the value of political connections since the decision to engage politically—such as making campaign donations—is endogenous. However, I will try to assess the value of successful donation, that is, conditional on donating to a candidate's election campaign - what is the effect of donating to the candidate who won.

One potential approach to answer this question is to use an event-study framework, comparing two groups of donating firms following an election. The first group would experience a positive shock to their political connection (i.e., the politician who they donated to, won the election), while the second group would serve as a control (i.e., their politician lost). However, this method has limitations. For example, critics might argue that election outcomes are often predictable, meaning no significant changes would be observed between the firms after the election—an issue that undermines the core assumption of the event-study framework. This concern is particularly relevant for stock market outcomes, as market prices largely reflect investors' expectations. The stock prices of firms that donated to a politician likely to win may adjust even before the election results are officially announced.

Therefore, I employ a regression discontinuity design (RDD) focused on closely contested elections to achieve a causal interpretation. The core identifying assumption here, following Lee (2008), is that in addition to candidate, regional, or temporal factors, an element of randomness affects the outcome in close elections. By comparing the performance of firms that supported narrowly winning candidates with those supporting narrowly losing candidates, I can capture the causal effect of a "potential" political connection becoming an "active" one.

If we assume that election outcomes are not predictable in the context of close elections, then stock market investors would not form anticipatory expectations, and market prices would only adjust after the election. This makes close elections an ideal setting for observing abnormal returns—changes in stock prices that cannot be explained by broader macroeconomic factors affecting the entire market.

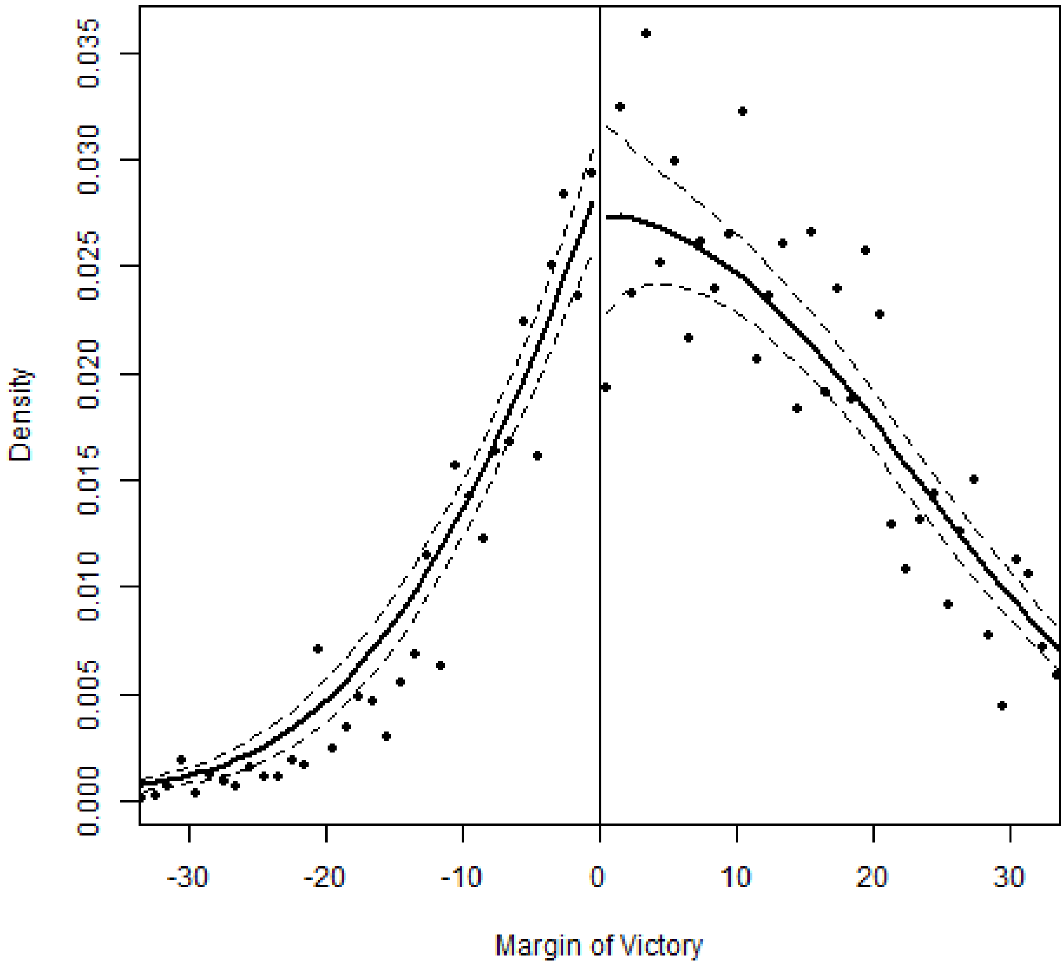
Implementing this method requires careful selection of elections that meet the criterion of randomness. Following Do et al. (2012, 2015), I include races decided by a margin of five percentage points or less. Below, I provide empirical evidence to support this choice. Moreover, as a robustness check, I follow Calonico et al. (2019) and use an optimal bandwidth selection method to determine which elections can be considered close.

Another identification assumption is the absence of systematic manipulation of the firms near the threshold. Testing for sorting around the threshold is a valuable tool for detecting potential manipulation. Following McCrary (2008), I examine the distribution of the running variable around the threshold. A discontinuous jump in the distribution would suggest that candidates are systematically more or less likely to win in close races. The absence of selection around the cutoff is well-documented in previous research. I aimed to demonstrate that my specific sample of elections also passes this test. Figure 2 presents the results of this test, including the statistic for the null hypothesis of no jump in the distribution. The results indicate no evidence of a density jump at the threshold.

Estimating the "political return" on each dollar donated might seem straightforward. However, it is unlikely that the donation itself fully captures the cost of establishing and maintaining a political connection.[4] Consequently, I estimate the causal effect of having a successful political connection instead. I assume that campaign donations reflect a deliberately chosen relationship between firms and politi-

[4]For example, Congressional investigations into the 2008 financial crisis revealed that Countrywide's "VIP Loan Program" provided preferential mortgage terms to influential figures, including Sen. Chris Dodd, then-chair of the Senate Banking Committee. These loans, with reduced interest rates and waived fees, were aimed at fostering support for Countrywide's business interests. The full report can be found here.

Figure 2: McCrary Test: Sorting Around the Winning Threshold




**Notes:** This plot present the McCrary test results in this sample of elections. Each point represents a bin. Bin size is 1. Discontinuity estimate (standard error): -0.008 (.0187).

cians, making them a reasonable indicator of connectedness. By analyzing abnormal returns, I can estimate the net benefit firms derive from these political connections.

# Data

To investigate the potential profitability of political connections for contributing firms, this study draws on a unique dataset constructed from three core sources: political donation records, election outcome data, and stock prices for the donating companies. These data sources were selected to capture the full landscape of each firm's engagement in the political sphere and to trace potential financial outcomes tied to this engagement. By merging these datasets, I created a comprehensive dataset that allows us to causally estimate the relationship between donations to a winning candidate and the firm's financial benefits.

The political donation records and the election outcome data were drawn from the Database on Ideology, Money in Politics, and Elections (DIME, Bonica (2024)), which provides a general resource for the study of campaign finance and ideology in American politics. This database contains most of the donations made by individuals and organizations to politicians in the United States. The stock prices data were drawn from the Yahoo Finance (2024) database.

In the United States, corporations are required to establish a Political Action Committee (PAC) if they wish to make donations to political candidates during election campaigns. Although firms must use PACs as intermediaries to legally channel donations, the PAC's name is not required to match the official name of the corporation exactly. This lack of a standardized naming convention presents a challenge in accurately identifying the PAC as the corresponding corporate donor, complicating efforts to trace donations back to their originating firms and merge them with stock performances.

Furthermore, a single firm may establish multiple PACs with different names, either due to changes over time or because different branches of the same parent company create PACs simultaneously. For example, the american multinational telecommunications holding company, AT&T, donated under the PAC name "AMERICAN TELEPHONE & TELEGRAPH COMPANY INC PAC AT&T PAC" until 2006, after which it transitioned to using the simplified name "at&t." This resulted in the 2006 election cycle featuring two distinct donor names for the same firm. Consequently, many donors with distinct names in the DIME database could be linked to the same firm.

Hence, a key challenge in constructing this dataset lies in accurately merging donor information from DIME with the stock symbols of the corresponding companies. To facilitate this matching process in reasonable time and to minimize human errors, I employed AI tools to accurately recognize and link donor names to their corresponding companies.

To minimize potential errors in AI-based identification of corporate donors, I implemented a cross-verification process using three distinct AI tools from three different companies, (OpenAI, 2024; Anthropic, 2024; Google, 2024). For each donor listed in DIME, I input the name as it appeared and tasked each AI tool with determining whether the donor was affiliated with a publicly traded company. If the tool identified a match, it was instructed to return the associated stock symbol. I considered a match reliable only when at least two of the three AI tools returned the same stock symbol, at which point I assigned the symbol to the donor, assuming it represented a publicly traded company. This method of verification caused me to drop about 4% out of my donors sample (3000 observations) because they were not reliable. However from a random sample of 100 observation out of those unreliable cases only 2% were successfully identified by one of the AI tool, the other 98% were mistakenly identified as a firm and were attached with a symbol that does not exists in the Yahoo Finance (2024) database.

Even with this verification method, errors cannot be entirely eliminated. To evaluate the extent to which the remaining dataset may have been misidentified, I selected a random sample of 100 identification results. Upon reviewing them, I discovered some errors in the AI-based classification. Approximately five percent of donors identified as publicly traded companies were, in fact, either different entities or not corporations at all (false positive). Additionally, around four percent of donors not classified as publicly traded companies were actually corporate entities (false negative). These error rates indicate some limitations in the AI-based matching process, though the multi-tool verification approach helped mitigate these inaccuracies to a degree.

The data from DIME is transaction-level election data for federal elections from 1980 to 2020, and I aggregated it by year. Table 1 shows summary statistics of donations to Congressional politicians from firm PACs. There is substantial increase in both the mean and total firm contributions to individual politicians and aggregate firm contributions over time.

Figure 3 displays the relationship between the proportion and the average proportion of donations to the winning candidate and their margin of victory. Overall, these variables show a strong correlation, as expected. Interestingly, the correlation becomes insignificant once the margin of victory drops from around 7%, implying that the elections in this sample (with victory margins under 5%) are not systematically predictable in advance. Still, about 60 percent of the donations go to the candidate who won even in a close election. To address this potential concern with my identification assumption, I examined whether the amount of donations exhibits a discontinuous jump around the threshold (margin = 0).

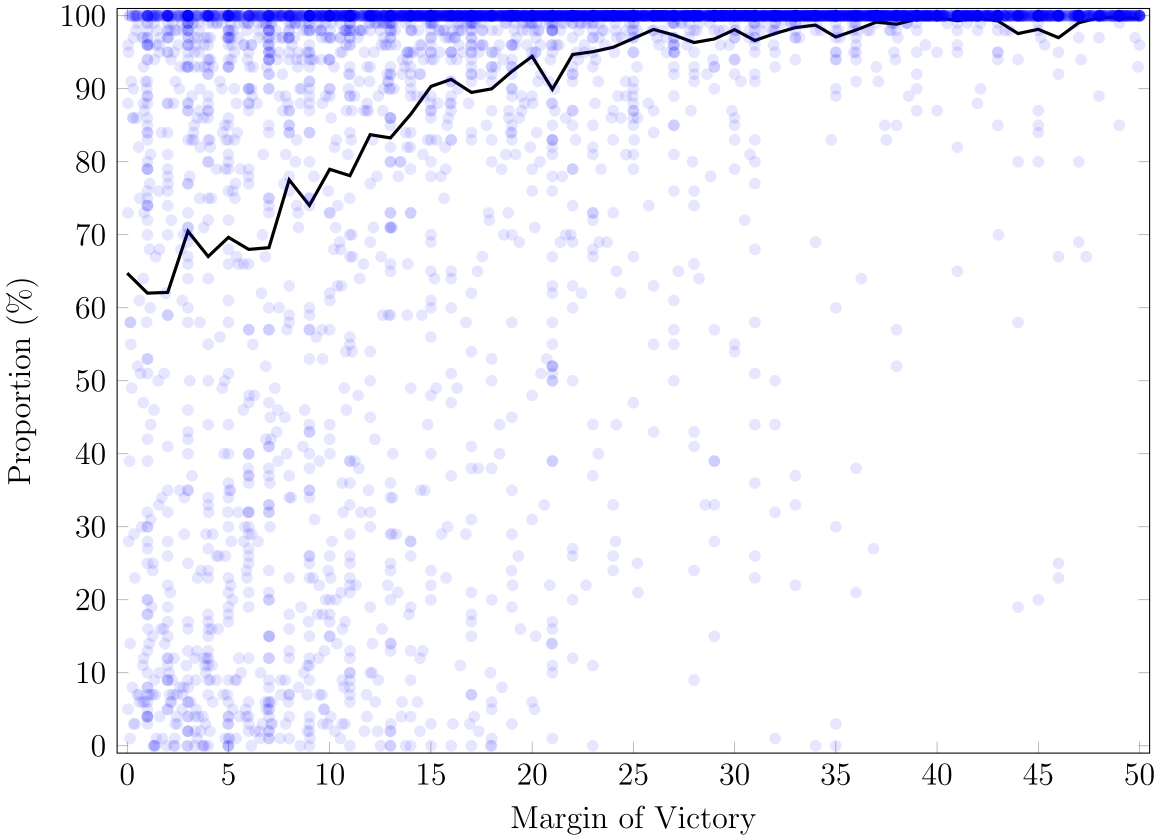
Figure 4 shows the relationship between the amount of (log) donations and the margin of victory. The linear fit suggests that there is no discontinuity in donation amounts as the margin crosses the threshold. The estimate is 0.043 and the confidence interval is between −0.025 and 0.111. This indicates that companies do not

Table 1: Firm's Donations Summary Statistics

| | Firm to individual politician | | | Aggregate firm contribution | | | |
|---|---|---|---|---|---|---|---|
| Year | Mean (thou) | St. Dev. (thou) | N | Mean (thou) | St. Dev. (thou) | N | Total (thou) |
| 1980 | 0.70 | 0.89 | 1,724 | 13.44 | 15.08 | 90 | 1,209.80 |
| 1982 | 0.77 | 0.82 | 2,459 | 18.16 | 18.50 | 104 | 1,888.63 |
| 1984 | 0.88 | 0.90 | 1,993 | 14.90 | 16.92 | 117 | 1,743.29 |
| 1986 | 1.10 | 1.33 | 2,486 | 20.90 | 26.73 | 131 | 2,737.89 |
| 1988 | 1.55 | 1.78 | 3,304 | 37.29 | 49.48 | 137 | 5,108.79 |
| 1990 | 1.77 | 1.99 | 2,547 | 34.39 | 45.44 | 131 | 4,505.53 |
| 1992 | 1.52 | 1.73 | 4,117 | 44.32 | 59.25 | 141 | 6,248.60 |
| 1994 | 1.64 | 1.90 | 3,882 | 43.78 | 64.40 | 145 | 6,348.64 |
| 1996 | 1.63 | 1.88 | 3,510 | 37.67 | 59.50 | 152 | 5,725.55 |
| 1998 | 1.92 | 1.97 | 2,494 | 30.83 | 40.97 | 155 | 4,778.52 |
| 2000 | 2.31 | 2.42 | 2,438 | 35.19 | 44.24 | 160 | 5,630.49 |
| 2002 | 2.81 | 2.79 | 2,798 | 37.23 | 59.81 | 211 | 7,855.19 |
| 2004 | 3.13 | 2.68 | 2,313 | 34.77 | 50.64 | 208 | 7,231.91 |
| 2006 | 3.39 | 3.37 | 2,777 | 39.40 | 61.08 | 239 | 9,417.62 |
| 2008 | 3.37 | 2.96 | 2,851 | 38.54 | 57.69 | 249 | 9,595.75 |
| 2010 | 3.42 | 2.96 | 5,477 | 50.92 | 104.51 | 368 | 18,738.94 |
| 2012 | 5.04 | 5.07 | 5,576 | 67.27 | 126.01 | 418 | 28,116.77 |
| 2014 | 5.57 | 7.46 | 6,804 | 80.84 | 168.92 | 469 | 37,912.30 |
| 2016 | 5.84 | 5.63 | 3,447 | 46.20 | 83.17 | 436 | 20,144.17 |
| 2018 | 5.97 | 5.28 | 4,426 | 58.22 | 105.02 | 454 | 26,430.30 |
| 2020 | 7.06 | 6.32 | 4,378 | 62.40 | 109.78 | 495 | 30,885.88 |

**Notes:** This table summarizes the donations from firms to individual politicians and aggregate donations from firms over the years. The mean, standard deviation, and total values are in thousands.

Figure 3: Proportion of Donations Received by the Winning Candidate

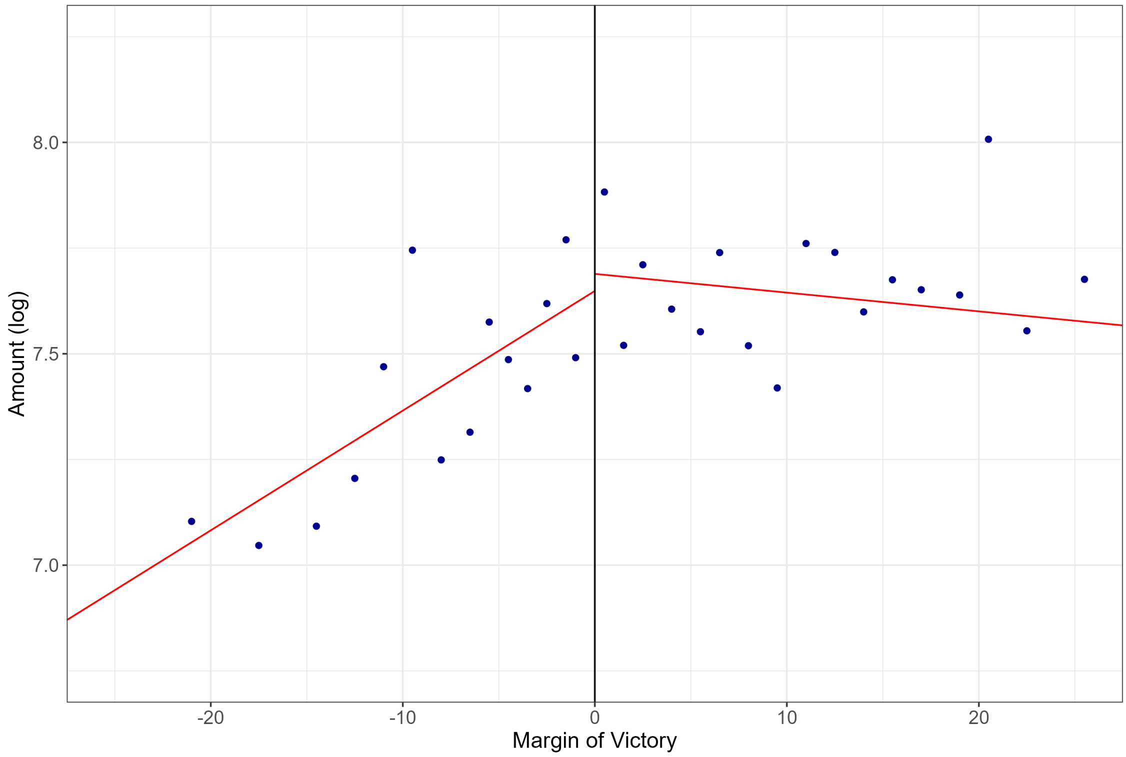



**Note:** This plot present the proportion (blue dots) and the average proportion (black line) of total donations (y-axis) against the margin of victory by which the candidate won the election (x-axis).

systematically adjust their donation behavior to favor winners in close races.

I collected daily stock price data from Yahoo Finance (2024) and calculated abnormal returns using the CAPM model, with the S&P 500 index serving as the proxy for market returns. The final and combined sample includes 4,010 donors that I managed to identify as 679 firms, that made 60,206 donations to general election candidates. To capture the election effect, I used two abnormal return windows: a (-1, +6) day window to align with prior research, and a shorter (-1, +1) day window for a closer assessment of the immediate election day impact (Kothari and Warner, 2007).

Figure 4: RD Plot - Donations Amount by Win Margin




**Notes:** This plot present the (log) amount of donations on the y-axis relative to the margin of victory on the x-axis. The red solid lines represents linear fit to the data, and the vertical black line marks the threshold for victory (margin = 0), RD estimate (SE): 0.043 (0.035).

# Analysis

In this section, I describe and present the results of the close election analysis. I begin by describing the sample and the variables that I used in this analysis. Next, I describe the RD model that I estimated and present the main results, followed by the results of the robustness and heterogeneous checks.

The sample includes 448 close elections from 1980 to 2020. The analysis focuses solely on the subset of firms that donated exclusively to either the winning or losing candidate.[5]

I define a dummy variable $Won$, which takes a value of one if candidate $j$ won a close election and a value of zero otherwise. I define another variable $Margin$ as the positive difference in vote share for a winning candidate or the negative difference in vote share for a losing candidate. For example, in a two-person race where the winner obtained 52% of the votes, his/her $Margin$ value would be +0.04 whereas the losing candidate's $Margin$ value would be -0.04. I run the following regression to estimate the value of "just winning" an election:

$$CAR_{i,j} = \beta_1 Won_j + f(Margin_j) + Won_j \times g(Margin_j) + X_j \bar{\gamma} + \epsilon_{i,j} \tag{1}$$

where $i$ indexes firms, $j$ indexes candidates, $CAR_{i,j}$ is the cumulative abnormal returns of firm $i$ that donated to candidate $j$, $f$ and $g$ are polynomial functions (linear or quadratic) of $Margin_j$ , and $X_j$ is a vector of control variables in the candidate level (state and election cycle).

Specifications (1)-(4) in Table 2 examine the (−1,+6) event window, while specification (5)-(6) examines the (−1,+1) event window. In this model $\beta_1$ capturing the average value difference associated with donating to a winner. The results show no significant gap between those who donated to winners versus losers. Standard errors, clustered by firm, indicate with 95% confidence that this gap is no larger than 0.5% and no smaller than -1%.

This finding is relatively small, given a benchmark of a 2% average absolute abnormal daily return and a 4% standard deviation. It is also small compared to other benchmarks in the literature; for example, an announcement for unexpected positive

[5] As Akey (2015) noted, firms that donated to both candidates (i.e. hedging firms) show no visible effect on abnormal returns, likely because the market had already priced in the likelihood of a connection becoming active post-election. However, hedging accounts for only 10% of the sample.

Table 2: General election CAR regression discontinuity results

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Event Window | (−1,+6) | (−1,+6) | (−1,+6) | (−1,+6) | (−1,+1) | (−1,+1) |
| Won | −0.001 | −0.001 | −0.001 | 0.001 | −0.002 | −0.001 |
| | (0.003) | (0.003) | (0.003) | (0.004) | (0.002) | (0.003) |
| Observations | 14,040 | 14,040 | 14,040 | 14,040 | 14,040 | 14,040 |
| $R^2$ | 0.028 | 0.028 | 0.028 | 0.029 | 0.035 | 0.035 |
| Functional Form | linear | linear spline | quadratic | quad. spline | linear spline | quad. spline |

**Notes:** This table shows the effect of a candidate's victory on abnormal returns using regression discontinuity (RD). The sample is limited to elections decided by a margin of 5% or less. The specifications vary by time window relative to the election day and the order of the local polynomial. The dependent variable is cumulative abnormal returns, and $Won$ is a dummy variable indicating a candidate's victory. All specifications include state and election cycle fixed effects. Standard errors clustered at the firm level in parentheses.

$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

earnings is associated with an average abnormal return of 5% (Chen et al., 1997).

Table 3 presents regression discontinuity estimates using an optimal bandwidth and bias-correction bandwidth selection method developed by Calonico et al. (2019). This approach ensures more robust and reliable inference by selecting bandwidths that balance bias and variance optimally. Notably, while the optimal bandwidths determined by this method are substantially larger than the 5% bandwidth used in the previous table, the null effect persists across all specifications. Furthermore, the results remain strikingly consistent with those presented in the prior table.

Figure 5 illustrates the main finding based on the linear estimate. Each point

Table 3: General election CAR regression discontinuity results - Optimal Bandwidth

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Event Window | $(-1,+6)$ | $(-1,+6)$ | $(-1,+6)$ | $(-1,+6)$ | $(-1,+1)$ | $(-1,+1)$ |
| RD estimates | $-0.002$ | $-0.0024$ | $-0.0025$ | $-0.0027$ | $-0.0012$ | $-0.0014$ |
| | (0.0027) | (0.0027) | (0.0031) | (0.003) | (0.002) | (0.002) |
| Observations | 30,146 | 39,346 | 37,419 | 46,336 | 39,293 | 46,076 |
| Local-Polynomial Order | linear spline | linear spline | quad. spline | quad. spline | linear spline | linear spline |
| Bandwidth Type | Optimal | Bias-Correction | Optimal | Bias-Correction | Optimal | Bias-Correction |
| Bandwidth (%) | 12.081 | 17.569 | 16.436 | 23.913 | 17.548 | 23.528 |

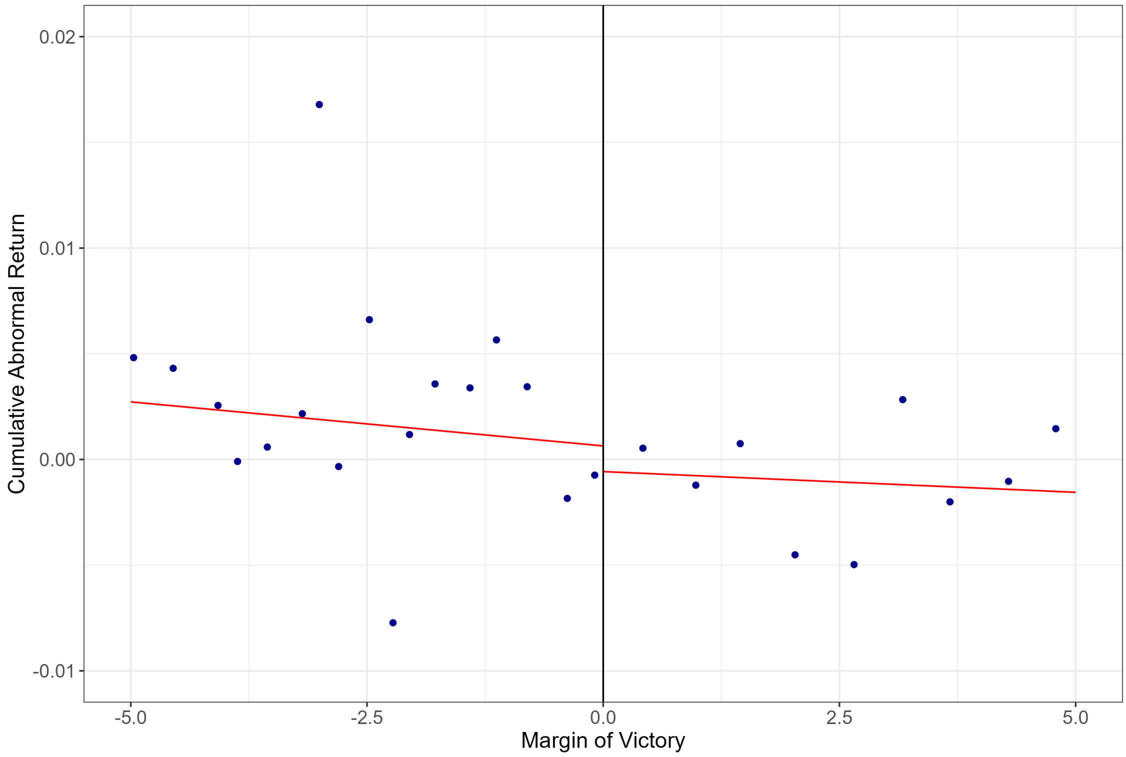
**Notes:** This table shows the effect of a candidate's victory on abnormal returns using RD with optimal bandwidth selection. The specifications vary by time window relative to the election day and the order of the local polynomial. The dependent variable is cumulative abnormal returns. All specifications include state and election cycle fixed effects. Standard errors clustered at the firm level in parentheses.

$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

represents the average of the cumulative abnormal returns within bins of equal size. Linear fit is shown alongside the bins' averages. The figure reveals no statistically significant jump in abnormal returns near the threshold.

These results contrast with previous studies that reported a significant and robust positive effect for donating to the winning candidate (Cooper et al., 2010; Akey, 2015). I found these null results despite adhering to standard practices in regression discontinuity literature and carefully estimating a series of different models. Moreover, the use of optimal bandwidth selection further strengthens my results and ensured that those results are not due to any arbitrary decisions. The differences between my findings and those of previous studies may stem from the fact that this analysis is based on a broader and more extensive dataset, capturing a wider range of elections,

Figure 5: RD Plot - Cumulative Abnormal Returns of Firms by Win Margin




**Notes:** This plot present the effect of a candidate's victory on abnormal returns using RD. The x-axis represents the margin of victory, while the y-axis represents the cumulative abnormal returns. The solid lines represent a linear regression fit for each side of the cutoff. The vertical black line represent the cutoff point for election results. RD estimates (SE): $-0.0006$ (0.0066).

firms, and economic conditions. This allows for a more comprehensive estimation of the effect of donating to the candidate who won, reducing the likelihood that results are driven by a specific subset of data.

A null result in estimating the value of a firm's connection to a winning candidate necessitates a thorough investigation to ensure robustness and uncover any potentially hidden patterns. It is important to look for heterogeneous effects that may vary across different political contexts, such as party affiliation or incumbent versus challenger dynamics. For instance, connections to incumbents may yield distinct effects from those associated with challengers, given the incumbents' established political influence. Additionally, analyzing trends across states and election cycles may reveal systematic patterns that a single aggregate analysis could overlook. Understanding these factors can clarify if and when donations to winning candidates are most likely to yield measurable benefits.

Table 4 reports the results of the heterogeneous effects examination across different political parties and incumbency statuses. The results show no significant gap between those who donated to winners versus losers regardless of the candidate's position or political alignment. Moreover, looking at the standard errors we can conclude with 95% confidence that the effect is no more than 0.5% and no less than $-0.5\%$.

Figure 6 reports the results of the examination of heterogeneous effects over time. Those are the results of a linear spline regression model with an interaction term between the treatment variable ($Won$) and the election cycle. No significant trend emerges from this analysis. Most of the cycles exhibit no effect, and, if anything, the only two cycles that are statistically significant show a negative effect.

Figure 7 shows a map that reports the results of the examination of heterogeneous effects across U.S. states. Those are the results of a linear spline regression model with an interaction term between the treatment variable ($Won$) and the candidate's state. The number in the center of every state is the estimator from the regression and the color of the map indicates the level of statistical significance. The white color indicates a null effect. As we can see, no significant effect emerges from this analysis. Most of the states exhibit a null effect, and in 3 cases the $p$-value is between 5% and 10%. The only exception is Vermont, which stands out as an outlier due to a single Senate race in 1980. In this election, Lockheed Martin Corporation donated to the Democratic senator Patrick Joseph Leahy, who won with a 2% margin. On that day, Lockheed experienced a 2% abnormal return. There were no other close elections in

Table 4: General election CAR regression discontinuity - Heterogeneous effects

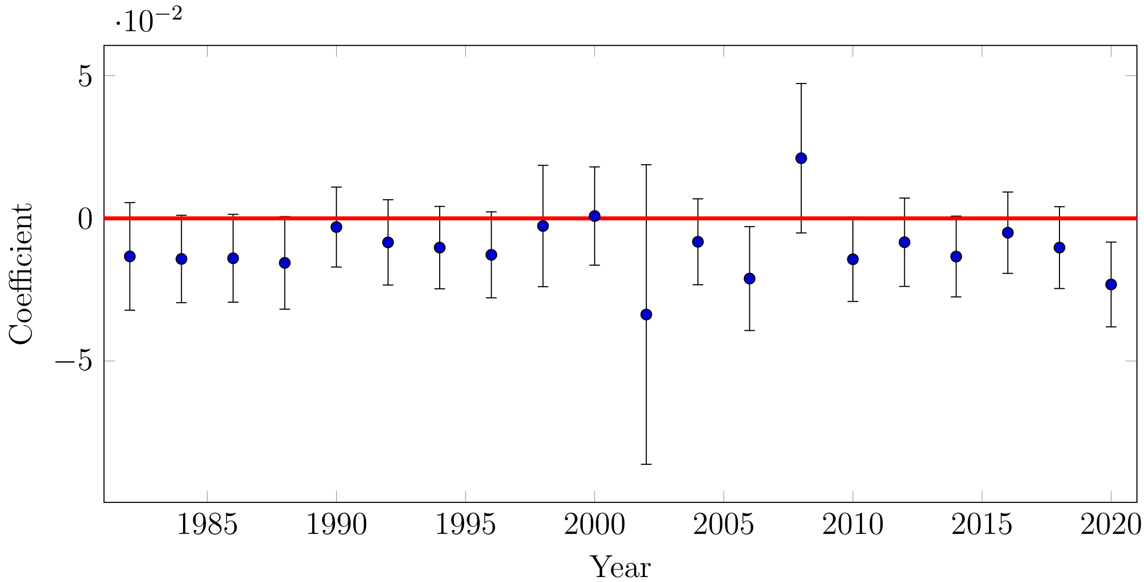
| | (1) | (2) | (3) |
|---|---|---|---|
| Won | −0.002 | −0.004 | −0.004 |
| | (0.003) | (0.005) | (0.005) |
| Won × Democrat | 0.001 | | −0.001 |
| | (0.002) | | (0.002) |
| Won × Incumbent | | 0.003 | 0.003 |
| | | (0.005) | (0.005) |
| Observations | 14,040 | 14,040 | 14,040 |
| $R^2$ | 0.035 | 0.035 | 0.036 |

**Notes:** This table shows the heterogeneous effects of a candidate's victory on abnormal returns using RD. The sample is limited to elections decided by a margin of 5% or less. The dependent variable is cumulative abnormal returns. *Won* indicates a candidate's victory, *Democrat* indicates the candidate belongs to the Democratic Party, and *Incumbent* indicates the candidate held office during the election. All specifications use a (−1, +1) time window around election day, a linear spline as the local polynomial, and include state and election cycle fixed effects. Standard errors clustered at the firm level in parentheses.

*p<0.1; **p<0.05; ***p<0.01

Vermont, and no other firms donated to Leahy.

Figure 6: Heterogeneous Effects Over Time

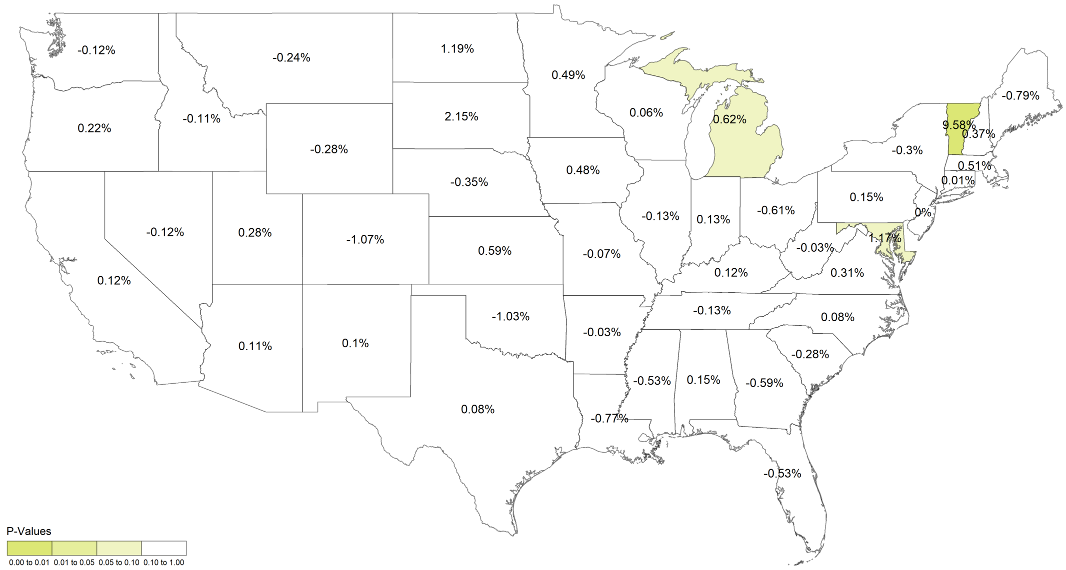



**Notes:** This plot present the heterogeneous effects of a candidate's victory on abnormal returns using RD. The sample is restricted to elections decided by a margin of 5% or less. The points indicate the estimated effect for each year, accompanied by 95% confidence intervals (calculated using a clustered standard errors at the firm level). The regression model corresponds to Equation 1, incorporating an interaction term between the election cycle and $Won$. This specification employs a $(-1, +1)$ time window around election day, a linear spline as the local polynomial, and includes state and election cycle fixed effects.

Furthermore, a deeper dive into the data is critical, particularly in cases where one might anticipate the strongest effects of political connections. If we assume that a winning candidate might act favorably toward contributing firms out of indebtedness, we would expect the highest returns on donations in situations where firms provided substantial financial support.

Strong effects may also emerge when firms concentrate their donations on a small number of candidates, especially because the election outcome is uncertain. In contrast, firms that contributed to numerous candidates might see weaker effects, as the market could reasonably anticipate that at least some of these candidates would succeed. Examining these cases could illuminate under which conditions, if any, political

Figure 7: Heterogeneous Effects Across U.S. States




**Notes:** The map present the heterogeneous effects of a candidate's victory on abnormal returns using RD. The sample is restricted to elections decided by a margin of 5% or less. The numbers indicate the estimated effect for each state and the map is shaded according to the statistical significance of its estimator (calculated using a clustered standard errors at the firm level). The regression model corresponds to Equation 1, incorporating an interaction term between state and $Won$. This specification employs a $(-1, +1)$ time window around election day, a linear spline as the local polynomial, and includes state and election cycle fixed effects.

donations to the winning candidate are most profitable.

Table 5 reports the results of the examination of the effect for firms that provided substantial financial support. I examined it using two sub-samples: (1) cases where the firm donated an amount equal to the maximum donation within a firm-election cycle, and (2) cases where the firm's donation was at least $1,000. As shown, no significant effects emerge from this analysis; all sub-samples display a null effect, indicating no observable financial advantage linked to higher levels of donations in this context.

Table 5: Treatment Effect on CAR on subset by Donation Size

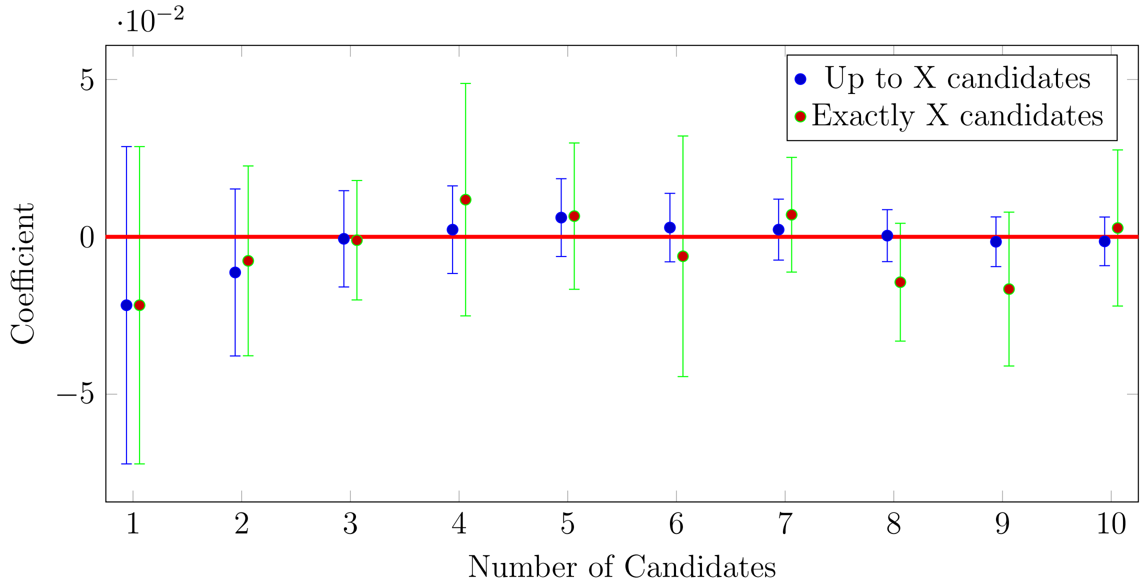
| | (1) | (2) |
|---|---|---|
| Won | 0.001 | −0.001 |
| | (0.004) | (0.003) |
| Donation Size | Max | 1000+ |
| Observations | 3,964 | 11,762 |
| $R^2$ | 0.052 | 0.038 |

**Notes:** This table shows the heterogeneous effects of a candidate's victory on abnormal returns using RD. The sample is limited to elections decided by a margin of 5% or less. The dependent variable is cumulative abnormal returns. $Won$ indicates a candidate's victory. Specification 1 restricts the sample to cases where the firm donated an amount equal to the maximum donation within a firm-election cycle. Specification 2 restricts the sample to cases where the firm's donation was at least $1,000. All specifications use a $(-1, +1)$ time window around election day, a linear spline as the local polynomial, and include state and election cycle fixed effects. Standard errors clustered at the firm level in parentheses.

$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Figure 8 displays the estimated treatment effects on a subset of firms, divided into two groups. Firms who donated to a specific number of candidates (e.g. a subsample of all the firms who donated to exactly two candidates in a given election cycle) and all the firms that donated up to that number (e.g. a subsample of all the firms who donated to up to two candidates in a given election cycle). The presented confidence interval is of the treatment variable ($Won$). As we can see, no significant effect arises

Figure 8: Results Over Number of Connections




**Notes:** This plot present the effects of a candidate's victory on abnormal returns using RD. The sample is limited to elections decided by a margin of 5% or less and includes firms that donated to up to X candidates (blue) or exactly X candidates (green). The points indicate the estimated effect for each number of political connections, accompanied by 95% confidence intervals (calculated using a clustered standard errors at the firm level). All specifications employ a $(-1, +1)$ time window around election day, a linear spline as the local polynomial, and include state and election cycle fixed effects.

from this analysis, all of the subsets exhibit a null effect.

# Discussion and Conclusion

Corporate donations to political campaigns are widespread and have grown significantly over the past four decades, yet their impact on firms' financial outcomes remains a topic of debate. This paper investigates the relationship between corporate political donations and firms' financial performance, focusing on the causal effects of donations to winning candidates on the abnormal returns of donating firms. By employing a regression discontinuity design, I was able to provide robust evidence on whether such donations yield abnormal returns for the firm.

The main analysis could not find any statistically significant effect and indicated that any potential impact is smaller than 0.5%, making it economically insignificant. This result holds consistently across various different robustness checks and heterogeneous effects analysis. These findings challenge earlier literature (Akey, 2015; Cooper et al., 2010) that suggests a positive relationship between political connections and financial outcomes. However, those studies relied on correlative analyses or small, non-representative samples, whilst this research is grounded in a comprehensive dataset covering all U.S. elections over the last 40 years.

These results support the second hypothesis on indirect connections, suggesting that firms making political donations may face higher agency costs. In this view, managers contribute to strengthen their political ties as a safeguard for future career opportunities rather than to benefit the firm. Consequently, no causal effect of donations on firm returns would be expected, aligning with the null results found in this study.

It is also possible that political connections do not necessarily translate into immediate or measurable financial gains reflected in stock market performance. Instead, firms may benefit from political ties through other channels, such as regulatory advantages, policy influence, or easier access to government contracts (Faccio, 2006; Bertrand et al., 2020). These benefits, while valuable to the firm, may not be directly observable in short-term stock returns, especially if investors do not perceive them as immediate drivers of firm value. As a result, the impact of political donations may manifest in ways that are not captured by abnormal stock returns.

One limitation of this study is that the political connections were defined using only donations; this definition may oversimplify the dynamics at play. Future studies may adopt a more nuanced approach to defining political connections. For instance, a political connection may be established when a firm donates to a politician with whom it shares either a vested interest or a common ideology (Akcigit et al., 2023).

When a firm donates to a politician, it is often seen as a direct connection between money and power in public opinion. However, the actual effect of such donations on firm value is more complex; future research should adopt a more comprehensive approach to understanding the ways in which political connections shape corporate outcomes.

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