NBER WORKING PAPER SERIES

THE PRICE OF POLITICAL TIES: REPUTATIONAL RISK AND THE STRATEGIC DIVESTMENT OF CORPORATE PACS

Eric A. Baldwin
Takuma Iwasaki
John J. Donohue
Charlie Grabois

Working Paper 35494
http://www.nber.org/papers/w35494

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2026

This work received no external funding. All research-related expenses were supported by Stanford University. All authors affirm that no conflicts of interest exist with respect to this research. The Stanford University Institutional Review Board has determined that this study does not involve human subjects as defined in 45 CFR 46.102(e) and therefore does not require full review by the Institutional Review Board. This determination was made on April 03, 2026. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2026 by Eric A. Baldwin, Takuma Iwasaki, John J. Donohue, and Charlie Grabois. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

The Price of Political Ties: Reputational Risk and the Strategic Divestment of Corporate PACs
Eric A. Baldwin, Takuma Iwasaki, John J. Donohue, and Charlie Grabois
NBER Working Paper No. 35494
July 2026
JEL No. C23, D22, D72, G32, H32, L21, M14, P10

ABSTRACT

Political contributions generate access and influence for firms, but their public visibility exposes firms to reputational risk. We study how firms adjust their political spending when the reputational cost of political ties rises sharply. To identify this response, we exploit fatal school shootings and mass shootings as exogenous shocks to the salience of gun violence in the United States. We implement a staggered difference-in-differences design on a panel of corporate PAC contributions to U.S. House candidates, 2000–2024. We find that corporate PACs divest selectively and temporarily following gun violence shocks. Contributions to Republican candidates fall by 70.3% after fatal school shootings in competitive districts and return to baseline within nine months, with no substitution toward Democratic candidates. A parallel penalty of 60.9% emerges for Republicans in safe Democratic districts but is absent in safe Republican districts. Mass shootings generate similar perturbations in corporate contributions. These patterns indicate that firms withdraw only where the reputational risk of continued association is high or its strategic value is low. The observed divestment appears across industries and is stronger for firms with greater consumer exposure. Our findings reveal that firms treat political ties as time-varying liabilities, temporarily withdrawing visible financial support when issue salience spikes and resuming once public attention fades, leaving firms' long-run political investment intact. Since public pressure is limited and dissipates quickly, and corporate divestment is transient rather than durably reallocated, the underlying financial incentives facing policymakers remain unchanged in the long run, sustaining the policy status quo.

Eric A. Baldwin
Stanford University
Stanford Law School
ericbaldwin@stanford.edu

Takuma Iwasaki
Stanford University
Stanford Law School
and Stanford Data Science
iwasakit@stanford.edu

John J. Donohue
Stanford University
Stanford Law School
and NBER
donohue@law.stanford.edu

Charlie Grabois
Stanford University
Stanford Law School
cgrabois@law.stanford.edu

I. Introduction

Corporate political contributions are both an instrument of political influence and a public signal of association. Firms cultivate political ties to influence policy, protect firm value, and secure access to officeholders (Fisman 2001; Grossman and Helpman 1994; Hassan et al. 2019; Kroszner and Stratmann 1998; Snyder 1990). Under federal disclosure requirements, contributions are discrete, attributable, and searchable (Ansolabehere et al. 2003). In ordinary periods, that visibility is largely latent. Contributions are public, but they are not especially salient outside of highly informed and specialized audiences. When public attention turns to the policy domain with which a firm's contributions are associated, those contributions can shift from political assets to reputational liabilities. To study how firms manage that tradeoff, we examine whether corporate PACs adjust their contributions when the reputational risk of political association rises.

Our empirical setting is gun policy in the United States. Gun violence has been the leading cause of death among American children each year since 2020 and has been among the leading causes of premature mortality for all Americans for decades, a pattern unique among industrialized nations (CDC 2026; Goldstick et al. 2022; Grinshteyn and Hemenway 2016). Fatal school shootings provide shocks that concentrate this crisis in a setting of extraordinary public visibility: they strike institutions in which tens of millions of families are directly invested, they command sustained media coverage, and they generate immediate political mobilization at both the elite and mass levels (Baldwin et al. 2026; Reny et al. 2023; Roemer 2023). Mass shootings provide a broader class of similarly situated shocks. The timing and location of these events allow us to estimate how corporate PAC contributions respond when the reputational cost of political association rises.

We construct a congressional district-month panel of corporate PAC contributions to U.S. House candidates from 2000 to 2024, linking the timing and location of each fatal school shooting to contribution flows in the affected district. The panel contains 130,500

observations spanning 468 districts.[1] Our main specification is a pseudo-Poisson maximum likelihood (PPML) difference-in-differences model. We focus on competitive districts, defined as those in which the previous House election was decided by five percentage points or less, because these are the races in which corporate PAC giving is both electorally consequential and likely to attract greater scrutiny.

We find that fatal school shootings produce a large, party-specific, and temporary contraction in corporate PAC contributions. Following a fatal school shooting, contributions to Republican candidates in the impacted competitive district fall by 70.3%, before returning to baseline within roughly nine months. Contributions to Democratic candidates do not increase. The absence of Democratic-side gains is inconsistent with a simple partisan reallocation, while the return to baseline is inconsistent with a durable change in corporate PAC alignment. The response instead points to targeted and temporary divestment by corporate PACs.

The response is also selective across electoral contexts. A parallel penalty of 60.9% emerges for Republicans in safe Democratic districts but is absent in safe Republican districts. Given that Republican candidates are more closely associated than Democratic candidates with opposition to gun regulation and with pro-gun policy positions, these findings are consistent with the theory that disclosed support for Republican candidates becomes especially reputationally costly when gun policy becomes salient. The contrast between safe Democratic and safe Republican districts is difficult to reconcile with a general retreat from Republican candidates. It is, however, more consistent with a reputational-risk mechanism in which corporate PACs reduce disclosed support where the reputational cost of association rises or the political value of continued support is lower.

We also look at whether the response varies across industry sectors and with consumer exposure. The Republican-side penalty appears across all fifteen industry sectors we test, with larger effects in more consumer-facing sectors but substantial declines even outside consumer-facing industries. Democratic-side estimates across the same sectors are mixed,

1. There are 435 districts observed in each month. Due to redistricting, some districts enter and exit our panel.

frequently near zero, and often positive. The Republican-Democratic asymmetry holds under both the baseline Poisson specification and the interactive fixed effects estimator. Placebo tests show that the response is concentrated among corporate PACs and does not appear among non-corporate PACs with no comparable cross-partisan reputation to protect. The sectoral breadth, consumer-exposure gradient, and placebo evidence suggest that the response is not driven by a narrow set of industries or by consumer backlash alone (Hong and Kacperczyk 2009; Jayachandran 2006).

Dynamic event-study specifications show a post-shooting path characterized by a temporary withdrawal and recovery. Permutation tests and leave-one-out analyses indicate that the baseline estimates are unlikely to be driven by chance or by a single event, district, or industry. Geographic spillover analyses show that fatal school shootings do not affect adjacent districts. The main result is also robust to alternative design and estimation choices, including stacked difference-in-differences, alternative staggered-treatment estimators, caps on large contributions, and alternative competitiveness thresholds. High-fatality mass shootings produce a similar pattern, indicating that the response extends beyond school-specific violence to other salient gun-violence shocks.

We also show that the response is unlikely to affect elections. The divestment documented here is not followed by durable electoral realignment in affected districts. This is not to say that contributions never matter for electoral outcomes, but rather that the temporary and selective withdrawal we observe does not appear to alter Republican candidates' electoral fortunes in any reliable way.

This paper makes two contributions. First, it adds reputational exposure to accounts of corporate political influence. Existing work establishes that contributions flow toward candidates positioned to deliver regulatory and legislative returns and that the value of political ties is priced into firm behavior (Bombardini and Trebbi 2011; Grossman and Helpman 1994; Hassan et al. 2019). We show that the value of those ties depends not only on their expected access returns but also on a time-varying reputational cost of association.

Exogenous shocks to issue salience produce large, temporary, and selective adjustments in corporate political spending even when underlying political objectives remain unchanged.

Second, the results speak to a longstanding puzzle in the study of money in politics. Ansolabehere et al. (2003) document that corporate PAC contributions are small relative to the regulatory and legislative stakes involved, a pattern that sits uneasily with standard access-based accounts. Our evidence points to a complementary explanation: the relevant cost of a disclosed contribution is not only the dollar amount transferred, but also the expected reputational exposure created by public attribution. Observed PAC contributions may therefore appear modest not because political access is unimportant, but because firms face reputational costs when support for a candidate becomes publicly salient.

Finally, the findings help explain why public salience shocks can produce visible but temporary changes in corporate PAC giving without durable political change. Fatal school shootings generate sharp reductions in disclosed corporate PAC support for Republican candidates, but the decline is temporary, is not substituted toward Democrats, and is not accompanied by persistent electoral realignment. The evidence therefore shows how public pressure can alter the timing and allocation of corporate PAC contributions while prior contribution patterns reemerge as attention fades.

The remainder of the paper proceeds as follows: Section II describes the data, identification strategy, and descriptive statistics. Section III presents the main results, alternative specifications, and robustness checks. Section IV develops the mechanism. Section V presents the implications and concludes.

II. Empirical Strategy

A. Data

We construct a panel at the congressional district and month level running from December 1999 to November 2024.[2] Our panel has 130,500 observations across 468 Congressional Districts.[3] We obtain contribution-level data covering direct and independent expenditures from OpenSecrets (2025), which we aggregate to the district-month level separately for each sector-to-party pair.[4] The raw data classifies donors into 434 categories based on the interests they represent. We handcode 290 of these categories into fifteen industry sectors; the remaining categories are excluded either because they represent narrowly defined interests with no clear sector analog or because they correspond to non-corporate interests.[5] Single-issue PACs are excluded, regardless of whether their policy positions align with corporate interests.[6]

In total, 1.63 million contributions from 4,180 unique donors are mapped to one of the fifteen sectors in our sample. Our primary outcome variables are total corporate contributions to Republican and Democratic candidates, calculated by summing contributions to each party across all fifteen industry sectors. Our secondary outcomes are total contributions in each sector-to-party pair.

To estimate models with district fixed effects that persist across redistricting cycles, we construct a master crosswalk that links districts across the 2000, 2010, and 2020 redistricting

2. Throughout this paper, references to year ranges in figures and tables reflect election cycles rather than calendar years. A range of 2000–2024 indicates that the sample runs from December 1999 through November 2024.

3. There are 435 districts observed in each month. Due to redistricting, some districts enter and exit our panel.

4. For example, one sector-to-party pair would be agriculture-sector contributions to Democrats.

5. Examples of narrowly defined interests: greeting card publishing, laundry and dry cleaners, and funeral services. Examples of non-corporate interests: clergy and religious organizations, teachers unions, and drug prohibition single-issue advocates.

6. E.g., defense shipbuilders like Bath Iron Works are included in the defense sector while peace-through-strength advocacy organizations like the American Security Council are not.

cycles based on population overlap, assigning each unique district lineage a persistent district identifier.[7]

To ensure each point in the U.S. corresponds to exactly one congressional district in every month, we use a next-election convention to ensure that all variables within each district-month reflect the same geographic unit. When a new district is created, it is added to our sample in the December two calendar years before its first election.[8] Contributions to candidates seeking office in newly created districts are thus observed in the panel. When states lose a congressional district, it is also treated according to this convention, and is last observed in the November of its last election.[9]

The next-election convention is followed for our treatment and control variables to ensure they reflect the same geographic unit as our outcome variable. We obtain data on fatal school shootings from Riedman (2025) and geocode each shooting to its district in the next Congress.[10] Demographic covariates are from the U.S. Census Bureau, and follow the same next-election convention (Ruggles et al. 2025).[11] Election returns are sourced from Leip (2025). By applying the next-election convention consistently across all variables, each location in the United States maps to exactly one congressional district in every month of the sample, and the panel contains exactly 435 districts in every month, eliminating all ambiguity in how

7. For additional details on the construction and validation of the crosswalk, see Appendix A, Subsection 1.

8. For example, Arizona gained its 7th Congressional District following the 2000 Census. This district could be first observed in a district panel in November 2002 (when it first elected a representative), January 2003 (when that representative took office), or December 2000 (when contributions could first be made in anticipation of the November 2002 election). In our panel, we use December 2000.

9. For example, California lost its 53rd Congressional District following the 2020 Census, so no election was held for the seat in November 2022. Thus, the district is last observed in November 2020, even though it had a representative in office until January 2023.

10. For example, the Mevers School of Excellence shooting occurred in Goose Creek, SC on May 26, 2022. In the 117th Congress, Goose Creek was part of South Carolina's 6th Congressional District. However, in the 118th Congress, elected in November 2022 (the next election after the Mevers shooting), Goose Creek was part of South Carolina's 1st Congressional District. Hence, the Mevers shooting is mapped to the 1st District.

11. For example, the percent Black variable for South Carolina's 1st District in May 2022 reflects the 2022 racial composition of the area that would become the 1st District under the 118th Congress boundaries, ensuring that the demographics of Goose Creek—the site of the Mevers shooting—factor into its value.

contributions, shootings, and demographic characteristics are assigned to geographic units across redistricting cycles.[12]

B. Identification

We use a static Poisson pseudo-maximum likelihood (PPML) model with two-way fixed effects (Santos Silva and Tenreyro 2006). Leveraging fatal school shootings as exogenous and quasi-random shocks to the salience of gun violence, we estimate how corporate PACs adjust contributions to Republican and Democratic candidates in affected districts. To assess pre-treatment trends and confirm robustness to staggered treatment, we employ dynamic event study specifications and alternative estimators (Borusyak et al. 2024; Cengiz et al. 2019; Goodman-Bacon 2021; Liu et al. 2024).

$$E(\text{Contrib}_{dm}|\cdot) = \exp(\gamma_d + \lambda_m + \delta \text{FSS}_{dm} + x'_{dm}\beta) \tag{1}$$

Our baseline model estimates how corporate contributions in a district are altered in the months following a fatal school shooting in that district (Equation 1). Congressional districts are indexed as d, and months by m. Our outcome (Contrib_{dm}) is total corporate contributions in district d in month m. We estimate the model separately for contributions to Republicans and to Democrats. We also estimate the same model for total contributions in each sector-to-party pair.[13]

Our treatment indicator is FSS_{dm}, a binary variable equal to one if district d experienced a fatal school shooting in month m or in the 23 months preceding m, and zero otherwise. We choose this treatment window to ensure that the treatment period overlaps with at least one election. We begin by restricting treatment status to districts that are competitive at the time of the shooting because the reputational mechanism we identify operates through

12. For additional details on the geocoding of shootings and the construction of the control variables, see Appendix A.

13. E.g., total contributions from the agriculture sector to Republicans.

the salience of fatal school shootings in electorally competitive environments.[14] Shootings that occur before a district becomes competitive are therefore not coded as treated, since the relevant reputational exposure is tied to the electoral context at the time of the event. A coefficient of δ on the treatment variable corresponds to a $100(\exp(\delta) - 1)\%$ change in expected contributions.

Controls are captured by x_{dm}. Election-related controls include the margin of the most recent House election and an indicator for whether a Democrat won that election. Demographic controls include the percentage of the population 25 and older with a bachelor's degree or more, the percentage of the total population that is white, the percentage of the total population that is black, the percent of the labor force (16 and older) that is unemployed, and inflation-adjusted median household income. Standard errors are clustered by district.

The sample is all competitive district-months between December 1999 and November 2024. We define competitive district-months as those with a margin equal to or less than 5% in the most recent prior election. Our focus on competitive races is chosen for two reasons. First, our theoretical framework predicts that reputational risk should be most acute in competitive races, as competitive races attract national attention that makes political ties more visible. Second, campaign finance dynamics vary between competitive and safe races. As a result, pooling races with such different contribution dynamics would risk confounding the effects of fatal school shootings with other dynamics.[15]

PPML is well-suited to our setting. Unlike OLS, PPML does not assume that the outcome variable follows any particular distribution (Santos Silva and Tenreyro 2006). The distributional assumptions of OLS fail, since the distribution of contribution totals across district-months is irregular: the modal contribution total is zero and positive contributions

14. If a fatal school shooting happens in a district and it then becomes competitive within 24 months, FSS_{dm} would still be zero for the months after the district becomes competitive.

15. Republicans in competitive races received $18,900 on average per month in corporate contributions, compared to $23,000 per month in safe Republican seats and $800 per month in safe Democratic seats. Democrats received $11,200 per month in corporate contributions in competitive races, compared to $16,000 per month in safe Democratic seats and $600 per month in safe Republican seats.

follow a right-skewed distribution.[16] No outcome transformation such as $\ln(1+y)$ can address the zero problem: any function $m(y)$ that is defined at zero and behaves like $\ln(y)$ in the limit will produce treatment effects sensitive to the units of y (Chen and Roth 2024). PPML does require dropping any district with zero contributions in all months, and any months with zero contributions in all districts. This is advantageous in our setting: districts or months with zero contributions in every observation provide no information about how fatal school shootings affect contribution behavior. For example, if Republicans in a given district received zero contributions before a fatal school shooting and zero after, that district isn't evidence against our corporate divestment hypothesis; it simply provides no information about corporate divestment behavior. PPML ensures the district does not affect our baseline coefficient estimates.

We estimate the following event study model to capture dynamic treatment effects and assess pre-treatment trends.

$$E(\text{Contrib}_{dm}|\cdot) = \exp\left[\gamma_d + \lambda_m + \sum_{\substack{k=-12 \\ k\neq -1}}^{12} \delta_k \mathbb{1}(\widetilde{m - m_d^*} = k) + x'_{dm}\beta\right] \tag{2}$$

In Equation 2, m_d^* is the month of the first shooting occurring in district d while it was competitive. We truncate $m - m_d^*$, the time elapsed since the shooting, to the range $[-12, 12]$ so that periods more than one year before or after the shooting are binned into endpoint indicators.[17] All other variables retain their definitions from Equation 1.

As recent literature suggests that two-way fixed effect estimators are biased under staggered treatment (Cengiz et al. 2019; Goodman-Bacon 2021), we estimate a static stacked difference-in-differences model. For each fatal school shooting in a competitive district, we define a stack s consisting of the treated district and all competitive districts in the same cycle that did not experience a fatal school shooting during the cycle.[18] Each stack covers only the election

16. For additional detail, see Figure B1.

17. Formally, $\widetilde{m - m_d^*} = \max(\min(m - m_d^*, 12), -12)$.

18. A district that experienced a shooting in one cycle may therefore serve as a control unit in stacks from other cycles, provided it was competitive and did not experience a shooting in the other cycles.

cycle in which the shooting occurred, so treatment runs from the month of the shooting to the end of the cycle rather than a fixed 24-month window. We then estimate a Poisson model with district-by-stack and month-by-stack fixed effects, addressing concerns about contaminated comparison groups in staggered difference-in-differences designs (Equation 3).

$$E(\text{Contrib}_{sdm}|\cdot) = \exp(\gamma_{sd} + \lambda_{sm} + \delta \text{FSS}_{dm} + x'_{dm}\beta) \tag{3}$$

Additionally, because each stack spans a single election cycle, candidates and district boundaries are fixed within every stack, meaning pre-shooting and post-shooting observations for each treated district come from the same electoral environment. While the main TWFE estimates partly establish each district's baseline using observations from cycles with different candidates on the ballot or different district boundaries, the stacked estimates do not, mitigating concerns about changing electoral environments within districts adding noise to the results. We use stacked difference-in-differences because it supports PPML estimation, but we additionally estimate several alternative difference-in-difference estimators robust to staggered treatment using log-linear OLS (Borusyak et al. 2024; Liu et al. 2024).

C. Descriptive Statistics

Our descriptive statistics show that corporations have cross-partisan political ties, are active in most competitive districts, and contribute throughout the election cycle rather than exclusively in the months immediately preceding elections. All fifteen industry sectors in our sample contributed to both Republicans and Democrats. While Republicans in competitive districts generally received more contributions than Democrats, all industry sectors except renewable energy contributed to both Republicans and Democrats in every cycle.[19] All but two sectors in our sample were active in at least 70% of competitive districts in every cycle,

19. Renewable energy did not contribute in the 2002 and 2006 cycles and contributed exclusively to Democrats in the 2004 and 2008 cycles. After 2008, the renewable energy sector contributed roughly equally to Republicans and Democrats, in line with the other fourteen industry sectors. For additional detail, see Figure B2.

and in at least 85% of competitive districts prior to 2016.[20] While contribution totals are elevated in September and October of even years, contributions are spread throughout the full two-year election cycle, meaning that candidates are actively receiving contributions well before the pre-election surge and that results are not driven solely by dynamics in the final months of each cycle.[21]

Covariates are balanced across treated and control districts, supporting our framing of fatal school shootings as quasi-random and unpredictable.[22] 55.1% of treated district-months had a Democratic victory in the most recent prior election, compared to 52.8% of control districts. The average margin in those elections was 2.76% in treated districts compared to 2.51% in control districts. There are slight differences in median income and percent white between treatment and control district-months, although we verify that controlling for these differences does not change the estimated effect of fatal school shootings on corporate PAC contributions.

III. Results

A. The Trigger Effect

Fatal school shootings reduce corporate contributions to Republicans by 70.3% in the baseline model, estimated on competitive district-months (Figure 1; baseline effect $= -1.215$, $p < 0.0001$). The effect remains negative and significant when winsorizing contribution totals at \$100,000 and \$20,000 (nominal dollars). While standard errors in PPML are robust to the variance structure of contributions, winsorization mechanically decreases the variance of contribution totals and ensures that the estimated effect is not driven by a small amount of outlier contributions. To address potential serial correlation in contributions, we estimate a

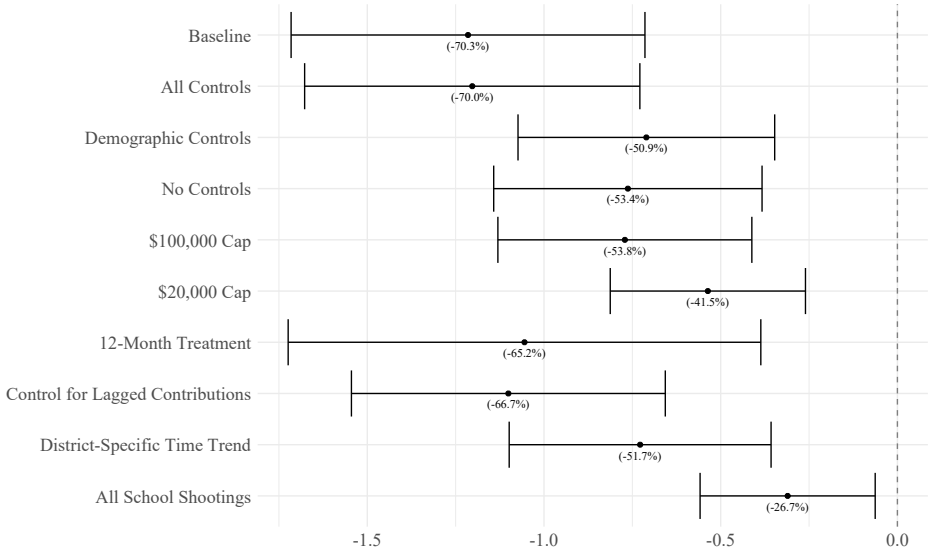
20. The exceptions are the renewable energy sector, whose coverage rose from 0% of districts in the 2002 cycle to roughly 60% of districts in 2024, and the hospitality sector, whose coverage fell from over 75% of districts in 2002 to just over 50% in 2024. For additional detail, see Figure B3.

21. For additional detail, see Figure B4.

22. For additional detail, see Table B1.

model controlling for total corporate contributions in the district in the six months preceding each observation. We also estimate a model including district-specific linear time trends. In each case, the estimated effect remains negative and significant, indicating robustness across specifications.

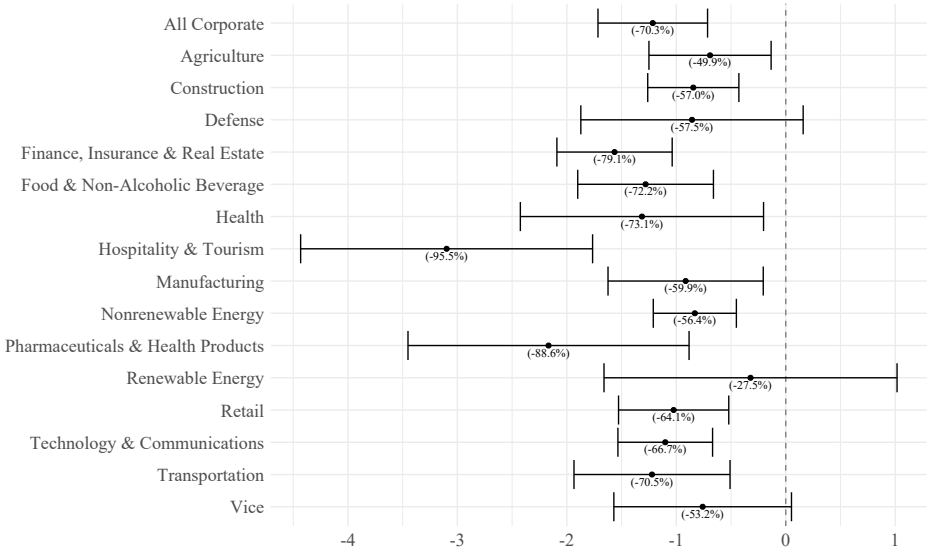
Figure 1: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Specifications, 2000–2024. Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions in all observations are excluded prior to estimation. When controlling for lagged contributions, the variance-covariance matrix could not be verified as positive semi-definite; interpret with caution. Standard errors are clustered by district.

We also test the impact of all school shootings on contributions, regardless of whether they generated a fatality, increasing the number of treated district-months from 256 to 1,327. The estimated effect on campaign contributions decreases from 70.3% to 26.7%, consistent with evidence that nonfatal school shootings generate less public outrage than fatal ones (Baldwin et al. 2026). However, the effect remains significant, corroborating our main finding that shocks increasing the salience of gun violence decrease corporate PAC contributions.

Figure 2: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Sectors, 2000–2024. Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

The impact of fatal school shootings on corporate contributions to Republicans is consistent across industry sectors (Figure 2). Twelve of fifteen sectors show a statistically significant reduction in contributions to Republicans following fatal school shootings; the remaining three show negative but imprecisely estimated effects. The consistency across sectors suggests the result is not driven by any particular sector's contribution patterns or by the specific way we aggregate donors into industry sector categories.

The breadth of this finding is striking: we find that every industry sector penalizes the Republican candidate following fatal school shootings in competitive districts over the past 25 years. If shootings truly had no effect on contributions, observing negative point estimates across all fifteen sectors, with twelve statistically significant effects, would be extraordinarily unlikely by chance alone.[23]

23. We formalize this claim with permutation tests in Section III, Subsection B. We also verify the robustness of the sector-disaggregated results to varied specifications in Appendix D, Subsection 1.

We also estimate the impact of fatal school shootings on corporate contributions to Republicans using a static stacked Poisson model. By using only never-treated districts as controls within each stack, we avoid the forbidden comparison problem that can arise in staggered difference-in-differences designs (Cengiz et al. 2019; Goodman-Bacon 2021). Additionally, because the stacks are each constructed within a single election cycle, each stack has two desirable properties: it is a balanced panel and each district in the stack has consistent election dynamics and boundaries each time it is observed. The former follows from the fact that competitiveness, which determines sample inclusion, is determined by the margin of the most recent prior election, which is fixed within a cycle. For this reason, election-related controls are collinear with district-stack fixed effects and thus excluded.

The stacked estimates are consistent with our main findings: fatal school shootings significantly reduce corporate contributions to Republicans across all specifications (Table 1; baseline effect $= -0.814$, $p < 0.002$), though the magnitude of the baseline stacked estimate (55.7%) is somewhat attenuated relative to the baseline TWFE estimate (70.3%). This attenuation likely reflects the more limited comparison group used in the stacked model.

Table 1: Effect of Fatal School Shootings in Competitive Districts on Contributions to Republicans Across 15 Sectors, 2000–2024. Static Stacked PPML Model.

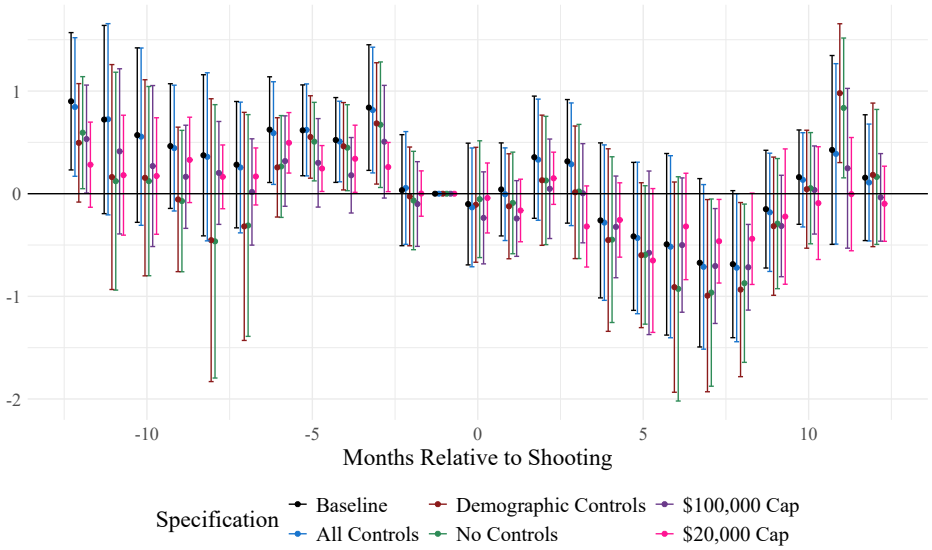
	Baseline	Demographic Controls	$100,000 Cap	$20,000 Cap
Fatal School Shootings	-0.814***	-0.780***	-0.525**	-0.447***
	(0.252)	(0.263)	(0.211)	(0.165)
Observations	12,684	12,684	12,684	12,684
Control Mean ($)	19,868	19,868	19,868	19,868

Note: static stacked pseudo-Poisson maximum likelihood difference-in-differences model; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; within each stack, districts and months with zero contributions in all observations are excluded prior to estimation. The treatment period runs from each shooting month to the end of the election cycle. Standard errors clustered by district in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

We next estimate the dynamic effects of fatal school shootings on contributions to Republicans. Relative to districts without shootings, contributions in districts with shootings begin to decline about four months after the shooting, with the strongest decline six to eight

months following the shooting (Figure 3). This delay makes sense: corporate PACs may plan political contributions in advance, and it takes time for corporations to observe the fallout of shootings and the potential for reputational risk. Importantly, contributions to Republicans return to baseline levels nine to ten months following the shooting, following a U-shaped post-treatment path. This demonstrates that fatal school shootings produce only temporary shifts in corporate spending.

Figure 3: Corporate Contributions to Republicans in Competitive Districts Return to Baseline Nine to Ten Months After Fatal School Shootings, 2000–2024. Dynamic PPML Model.



Note: dynamic Poisson model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

The pre-period coefficients reflect the choice of $t = -1$ as the omitted period, not a true pre-trend. Since $t = -1$ is a below-average contribution month, the remaining pre-period coefficients appear elevated as an artifact of the omitted reference period. Consistent with this interpretation, the coefficients are stable across the months preceding the shooting, rather than gradually sloping downward toward zero. Moreover, a genuine anticipatory pre-trend is implausible in this context, as corporate PACs cannot predict the timing and locations of school shootings. Using $t = -1$ as the omitted period attenuates the estimated post-period

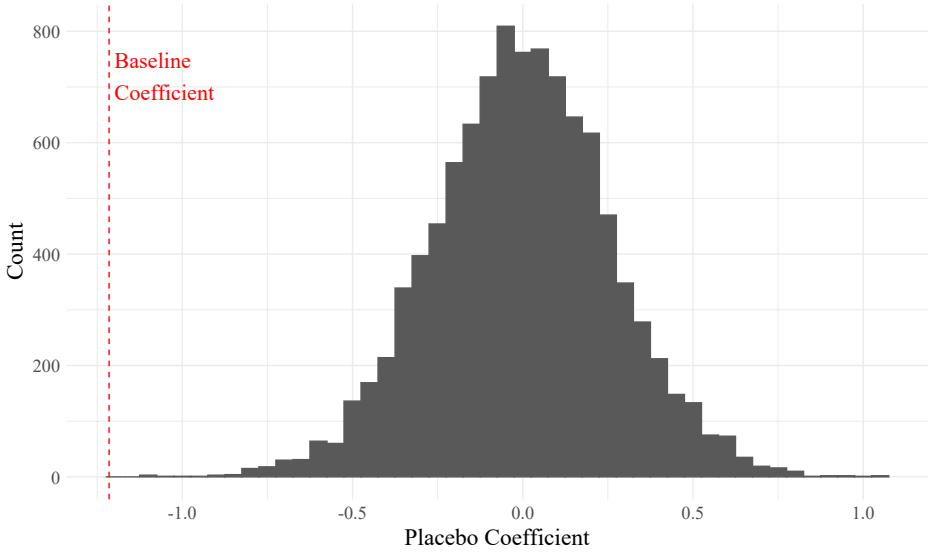
decline: a higher-contribution reference month would yield larger estimated treatment effects. Following from that logic, we show that expanding the sample of competitive districts to include those with margins up to 10% in the most recent election alleviates concerns about parallel trends without meaningfully affecting the U-shaped post-period trajectory (see Subsection B).

B. Robustness

The main results are robust to a wide range of alternative specifications, sample definitions, and estimation strategies. We conduct five sets of checks in this section. First, we implement nonparametric permutation tests and confirm that our coefficients exceed placebo estimates. Second, we expand our sample of competitive districts to include those with margins under 10%, rather than our baseline threshold of 5%. Third, we consider alternative estimators: log-linear OLS, imputation (Borusyak et al. 2024), and interactive fixed effects (Liu et al. 2024). Fourth, we show that using direct contributions only as our outcome does not change the estimated effect. Lastly, we verify that our results are robust to leave-one-out checks.

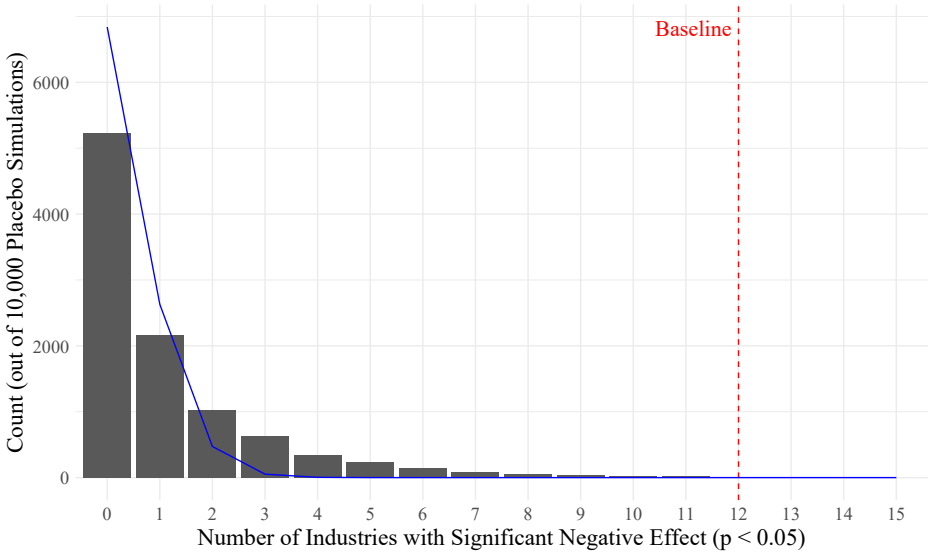
We conduct a nonparametric permutation test that inherits all of the unique statistical properties of our data. In each of 10,000 iterations of the test, we randomly generate 24 placebo shootings without replacement (the same number as in our sample); each shooting is equally likely to be in any competitive district-month. We then estimate the effect of these placebo shootings on total campaign contributions using our baseline static Poisson model. The baseline effect of -1.21 exceeds all 10,000 placebo coefficients, which range from -1.10 to 1.07 and are centered at zero (Figure 4).

Figure 4: Baseline Coefficient Exceeds All 10,000 Placebo Coefficients in Permutation Test, 2000–2024. Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; districts and months with zero contributions across all observations are excluded prior to estimation; dotted red line shows baseline effect, gray bars show distribution of placebo coefficients.

Figure 5: Number of Significant Negative Sector Effects Exceeds 99.88% of Placebo Runs, 2000–2024. Static PPML Model.



Note: gray bars show distribution of the number of sectors with significant negative placebo effects; blue line shows expected distribution assuming uncorrelated sector contributions; red line shows baseline number of significant negative sector effects.

We also conduct a permutation test to compute the likelihood of seeing twelve significant negative industry-disaggregated effects if the true effect of fatal school shootings on contributions is null. In each iteration, we randomly assign 24 placebo shootings to competitive district-months in our sample and compute the effect of the placebo shootings on contributions to Republicans from each of the fifteen sectors. Since the placebo shootings are assigned to real district-months, they inherit the cross-sector correlation of our data. Figure 5 shows the distribution of the number of significant negative sector effects across 10,000 iterations of the permutation test. The blue line corresponds to the expected distribution assuming independent sector effects: a binomial distribution with a success probability of 2.5% across 15 independent trials. While the distribution of significant negative sector effects has a noticeably higher expected value than the binomial distribution, the baseline of 12 significant negative sector effects exceeds all but 12 of the 10,000 runs of the permutation test, corresponding to a p-value of 0.0012. As an additional robustness check to verify that our inferences do not rely on asymptotic approximations, we compute score bootstrapped confidence intervals with Rademacher weights clustered at the district level; our results remain significant in this setting (Cameron et al. 2008; Kline and Santos 2012).[24]

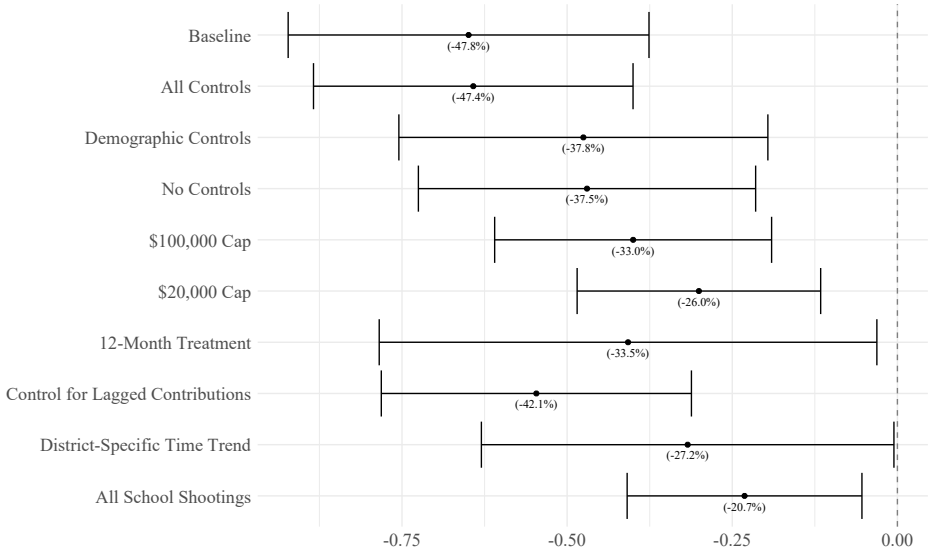
To test the sensitivity of our results to the 5% margin threshold used to determine district competitiveness, we estimate the impact of fatal school shootings on contributions using an expanded sample of competitive districts. In our main sample, only districts with a margin of 5% or less in the most recent prior election are included. By expanding this to 10%, we more than double both the number of observations and the number of fatal school shootings that trigger treatment.[25] Moreover, the 10% margin threshold increases the average district tenure in the sample from 43.3 to 63.6 months, giving treated districts more pre-shooting observations from which to establish a baseline contribution level.[26]

24. For additional detail, see Figure D1.

25. Observations increase from 8,004 to 16,260, and the number of treated district-months increases from 256 to 653.

26. For additional detail, see Figures B5 and B6.

Figure 6: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Specifications (10% Competitiveness Threshold), 2000–2024. Static PPML Model.



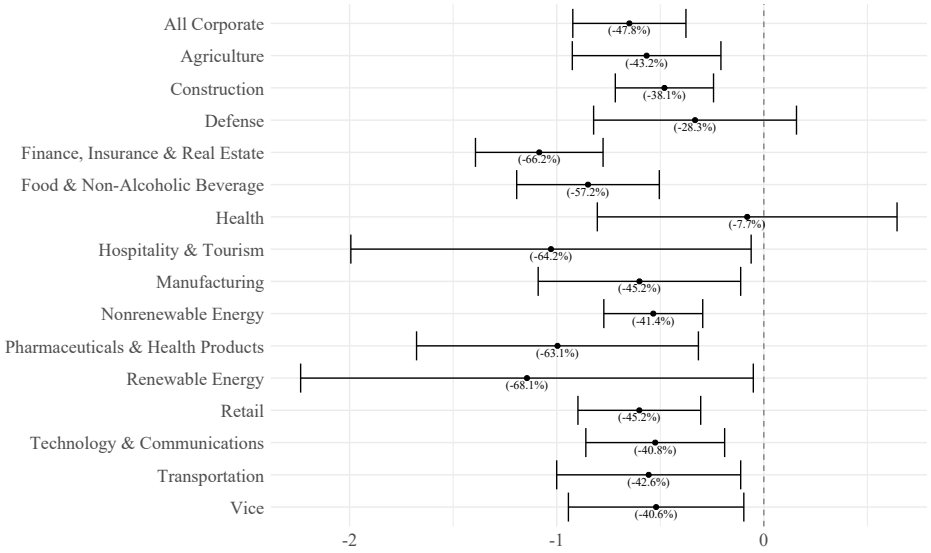
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions in all observations are excluded prior to estimation. When controlling for lagged contributions, the variance-covariance matrix could not be verified as positive semi-definite; interpret with caution. Standard errors are clustered by district.

The impact of fatal school shootings on contributions to Republicans remains significant and negative in the expanded sample across all 10 specifications (Figure 6). The baseline effect of fatal school shootings on contributions in the 10% sample is 47.8% (log effect = -0.65, $p < 0.001$), compared to 70.3% in the 5% sample. This attenuation is expected: the races in the 10% sample are less competitive on average and thus less likely to generate the public attention that drives our effects. The inclusion of districts with Republican margins between 5% and 10% in particular is likely to attenuate the estimated effect, as constituents in more strongly Republican districts are less likely to blame Republicans for fatal school shootings.

The sector-disaggregated results also hold: in the 10% sample, fatal school shootings have a negative impact on contributions for every industry sector, and a significant negative impact for 13 of the fifteen sectors, up from 12 in the 5% sample (Figure 7). The event study

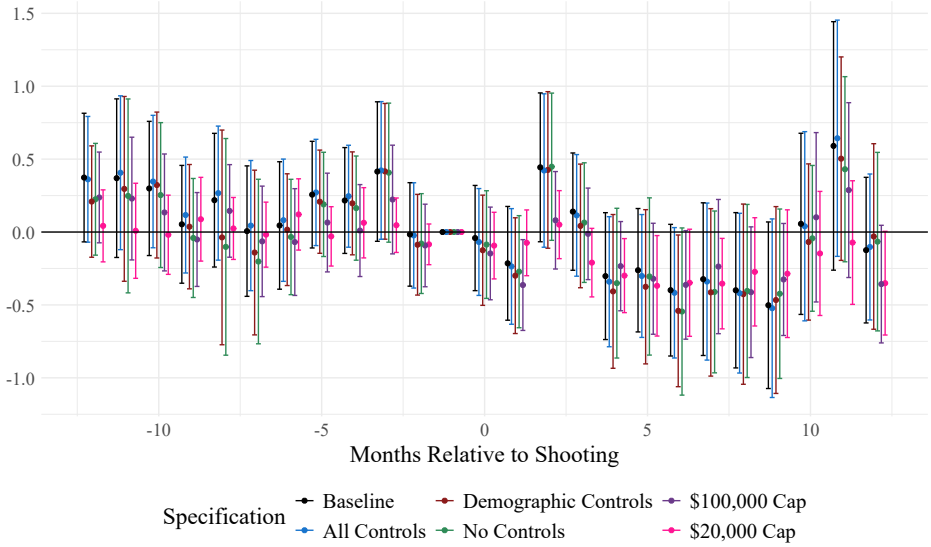
results have flat pre-trends and retain the same U-shaped post-treatment trajectory as the 5% model, suggestive of the same transient divestment pattern (Figure 8).

Figure 7: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Sectors (10% Competitiveness Threshold), 2000–2024. Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure 8: Corporate Contributions to Republicans in Competitive Districts Return to Baseline Nine to Ten Months After Fatal School Shootings (10% Competitiveness Threshold), 2000–2024. Dynamic PPML Model.



Note: dynamic Poisson model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Our results are also robust when using log-linear OLS instead of PPML to estimate the effects. While PPML can handle individual observations with zero contributions, it requires dropping any district with no contributions in all months, and any month with no contributions in all districts. This affects under 3% of observations for the sector-aggregated results, higher shares of district-months for the sector-disaggregated results, and a majority of district-months for two sectors: renewable energy and hospitality.[27] PPML's approach to zeros is justified in our setting: districts and months with zero contributions across all observations are uninformative about how fatal school shootings affect contribution behavior. However, it does not drive the results: the consistent negative effects are robust to log-linear OLS, which uses the full sample of 8,220 district-months. Effects remain negative and significant for ten of the fifteen sectors in our sample.[28]

27. Observation counts are reported in Table D1.
28. For additional detail, see Appendix D, Subsection 3.

The results are also robust to the use of alternative staggered difference-in-difference estimators: the imputation estimator developed by Borusyak et al. (2024) and the interactive fixed effects estimator developed by Liu et al. (2024). As the imputation estimator does not support non-absorbing treatment, each district is defined as treated after its first fatal school shooting, mirroring the dynamic Poisson model. The imputation results suggest a similar U-shaped post-shooting trajectory in contributions to Republicans, with the rebound reaching pre-shooting levels nine to ten months after the shooting.[29] The main advantage of the interactive fixed effects estimator is that it does not require absorbing treatment; it employs the same treatment definition and 24-month treatment period as the static Poisson model. The IFE results confirm that fatal school shootings decrease corporate contributions to Republicans.[30]

We also test the impact of fatal school shootings on direct expenditures only. In our data, independent expenditures are classified using two variables: the party of the candidate targeted by the expenditure and whether the expenditure supports or opposes that candidate. Independent expenditures in support of Republicans or in opposition to Democrats are classified as contributions to Republicans, and vice versa for Democrats. This characterization of independent expenditures would be inaccurate if a PAC was spending money opposing a certain politician to aid a primary challenger in the same party or to aid a third-party candidate running in the general election. As a robustness check, we examine the impact of fatal school shootings on only direct expenditures. The results are robust to excluding independent expenditures from the total.[31]

No single sector or treated district drives our main estimates. Leaving out individual industry sectors from total corporate contributions to Republicans does not move the estimated

29. For additional detail, see Figure D25, Appendix D, Subsection 4.
30. For additional detail, see Appendix D, Subsection 4.
31. For additional detail, see Appendix D, Subsection 5. Independent expenditure refers to contributions made to support a candidate indirectly but not made directly to a candidate and without any coordination between the candidate and the donor. Independent expenditures are uncapped. Independent expenditures are commonly referred to as "dark money" but are not the full universe of dark money. Throughout the paper we use the term "contributions" because we aggregate donations and independent expenditures.

effect of fatal school shootings on contributions to Republicans (Figure D39). We also perform a similar exercise leaving out individual districts affected by shootings. The only district whose removal noticeably moves the estimated effect is Iowa's 3rd Congressional District, although the effect remains negative and significant without this district. This district is unique as it experienced three fatal school shootings in quick succession between 2022 and 2024. This culminated in a student-led protest at the Iowa State Capitol in 2024 that garnered significant public and media attention (Fingerhut 2024). The concentration of three shootings in a single district over a short time span accentuates the acute reputational risk faced by firms and produces a larger estimated effect than a single shooting could generate. We conduct an additional leave-one-out analysis in which we exclude Iowa's 3rd District along with each of the other affected districts in the sample, confirming that the estimated effect is not sensitive to the removal of two districts.[32]

IV. Reputational Exposure and Selective Divestment

Our main results show that corporate contributions decline sharply after fatal school shootings, then return to baseline within nine months. However, this pattern alone doesn't prove our preferred explanation that firms are reacting to reputational risk. The same pattern could also be observed if firms simply cut political giving across the board after a shooting, if they shifted money from Republicans to Democrats rather than reducing total giving, or if the drop was concentrated in one specific candidate or district rather than Republicans as a group. We test each of these alternatives below.

A. Selective Withdrawal Across Electoral Contexts

The decline we document is specific to Republicans, and it varies in a structured way across types of districts. Three features of this pattern matter for identifying the mechanism:

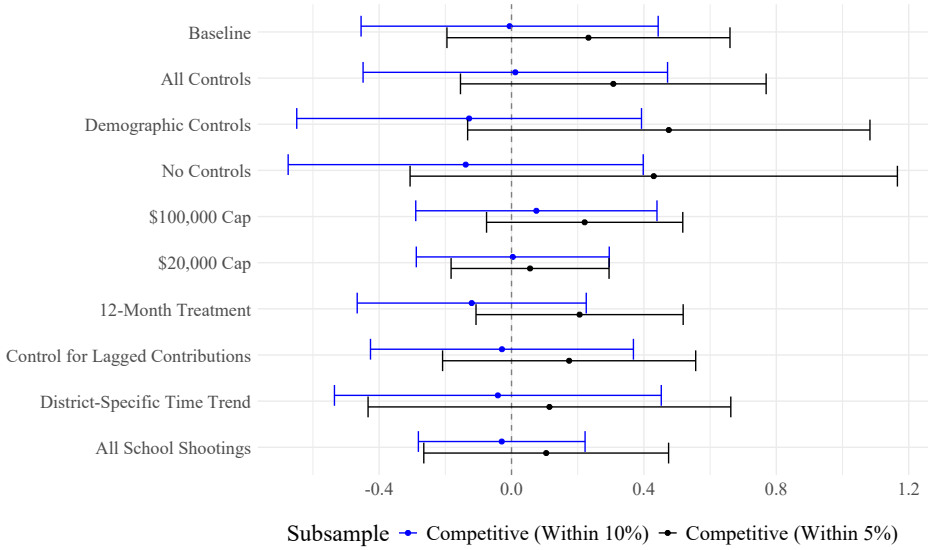
32. For additional detail, see Appendix D, Subsection 6.

first, contributions to Democrats do not rise to offset the drop; second, the size of the Republican-side penalty differs depending on the competitiveness of the district; and third, the penalty in competitive districts is the same whether the seat is currently held by a Republican or a Democrat.

Fatal school shootings produce no significant change in corporate contributions to Democratic candidates (Figure 9). This result matters because it undercuts two competing interpretations of the Republican-side decline. First, if in response to shootings, corporations shift support toward Democrats, whether because they expect Democrats to benefit electorally or because they genuinely revise their policy views on gun violence, one might reasonably expect the decline in Republican contributions to be matched by an increase in Democratic giving. Yet the estimated effects of fatal school shootings on contributions to Democrats are null and the confidence intervals are narrow enough to rule out effects comparable in magnitude to those on the Republican side. Indeed, the estimated effect on Democratic contributions is just -0.6% at the 10% competitiveness threshold.

Second, the same pattern cuts against a broader contraction in district-level giving: if shootings simply make impacted districts less attractive environments for political investment, contributions to both parties should fall. Instead, the decline is confined to Republican candidates. The evidence therefore points to a penalty specific to Republicans rather than a reallocation toward Democrats or a broader retreat from district-level political giving.

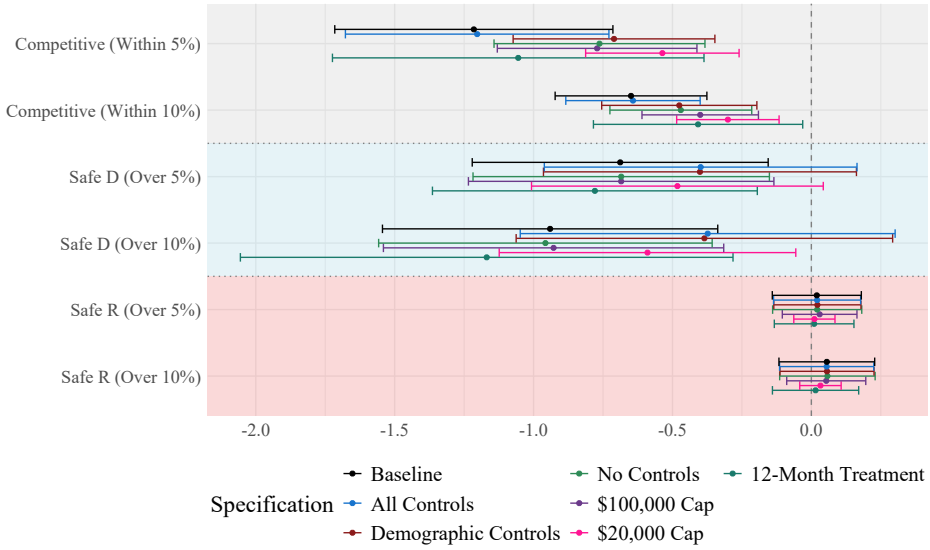
Figure 9: Fatal School Shootings Do Not Affect Corporate Contributions to Democrats in Competitive Districts Across Specifications and Competitiveness Thresholds, 2000–2024. Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. When controlling for lagged contributions, the variance-covariance matrix could not be verified as positive semi-definite; interpret with caution. Standard errors are clustered by district.

The Republican-side penalty varies across district types. The penalty is large in competitive districts, as shown in the main results (Section III), and it extends to safe Democratic districts, where Republican contributions fall by 60.9% (Figure 10). However, it is absent in safe Republican districts, where the point estimate is near zero and statistically indistinguishable from zero across specifications. If firms were simply pulling back from Republican candidates after a fatal school shooting, the penalty should appear in safe Republican districts as well. Instead, we observe that firms only withdraw in competitive districts, when support for Republicans is most visible, or in safe Democratic districts, where support is of lesser strategic value, while continuing to contribute in safe Republican districts, where attention is low and support guarantees access to a current or future policymaker. The pattern points to a selective response to reputational pressure rather than a broad retreat from political giving across all electoral contexts.

Figure 10: Fatal School Shootings Reduce Republican Contributions in Competitive and Safe Democratic Districts but Not Safe Republican Districts, 2000–2024. Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

We find party incumbency does not affect the penalty imposed on Republican candidates in competitive districts. The interaction between fatal school shootings and prior Democratic victory is near zero and statistically indistinguishable from zero across specifications (Table 2). The response does not appear to turn on whether the seat is currently held by a Republican or a Democrat. The effect appears in competitive districts where Democrats hold the seat and Republicans run as challengers, and vice versa. This suggests that corporate PACs are withdrawing visible support from Republican candidates more generally in competitive districts, rather than distancing themselves only from Republican incumbents.

Table 2: Heterogeneous Effect of Fatal School Shootings on Corporate Contributions to Republicans in Competitive Districts by Party Incumbency, 2000–2024. Static PPML Model.

	Baseline	All Controls	$100,000 Cap	$20,000 Cap
Fatal School Shooting	-1.221***	-1.205***	-0.751***	-0.521***
	(0.237)	(0.224)	(0.163)	(0.121)
FSS · Dem	0.030	0.010	-0.098	-0.056
	(0.446)	(0.462)	(0.419)	(0.352)
Observations	8,004	8,004	8,004	8,004
Control Mean ($)	18,784	18,784	18,784	18,784

Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. FSS · Dem is an interaction between the treatment indicator and an indicator for Democratic victory in the most recent prior election. Standard errors are clustered by district in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

B. Sector Heterogeneity

The decline in Republican contributions is found across industry sectors. Twelve of the fifteen sectors in our study show statistically significant reductions following fatal school shootings, and the remaining three also produce negative point estimates (Figure 2). The pattern is not confined to a narrow subset of sectors, which makes it difficult to attribute the result to the ideological preferences, particular market concerns, or historical contribution patterns of any one sector.

As an additional check, we test the relationship between sector consumer exposure and sector responsiveness to fatal school shootings. We expect that more consumer-exposed sectors will be more responsive to shootings, as they face a more direct reputational threat from visible political associations than business-to-business sectors. When consumers become politically mobilized, such as after fatal school shootings, firms that sell directly to consumers may face negative media attention and boycotts, affecting revenues (Mady et al. 2025). This logic parallels the underlying logic of greenwashing, which emphasizes the role of consumer trust and skepticism in motivating corporate reputation management (Persakis et al. 2025).

We expect business-to-business sectors to still show a response, as corporations in those sectors still have to preserve access to regulators, politicians, and business partners who may be aware of their campaign spending.

$$E(\text{Contrib}_{idm}|\cdot) = \exp(\gamma_{id} + \lambda_{im} + \theta FSS_{dm} + \kappa(FSS_{dm} \times CE_i) + x'_{dm}\beta) \tag{4}$$

To test for consumer exposure heterogeneity, we estimate Equation 4 via PPML. In this equation, i indexes industry sectors, d indexes districts, and m indexes months. Our consumer exposure index (CE_i), defined as the share of each sector's output purchased by final consumers, is constructed from the 2017 BEA Benchmark Use Table (Bureau of Economic Analysis 2023).[33] All other variables retain their definitions from Equation 1. The main coefficient of interest is κ, which captures the log-scale effect of consumer exposure on the treatment effect; a one-unit increase in CE_i multiplies the treatment effect by $\exp(\kappa)$. The percentage change in expected contributions following a fatal school shooting is $100(\exp(\theta + \kappa CE_i) - 1)$ for a sector i with consumer exposure CE_i.

Consumer exposure intensifies the divestment, albeit modestly. The interaction between treatment and the consumer exposure index is negative in every specification (Table 3), and the sector-disaggregated estimates become more negative as consumer exposure rises (Figure 11).[34] These patterns are directionally consistent with the idea that firms interacting more directly with households face somewhat stronger pressure to retreat when a fatal school shooting raises the salience of gun politics.

Consumer exposure amplifies the pressure to divest, but does not generate it. The fundamental source of this pressure is the reputational cost of public disclosure. When a fatal school shooting elevates the salience of gun violence, firms with visible ties to Republican candidates risk reputational damage from heightened public scrutiny. This can lead not only to backlash from consumers but also from regulators and other businesses. Sectors more

33. Full construction details are in Appendix A, Subsection 6.

34. For a version of Table 3 that does not weight observations by total industry contributions to competitive districts, see Table D5.

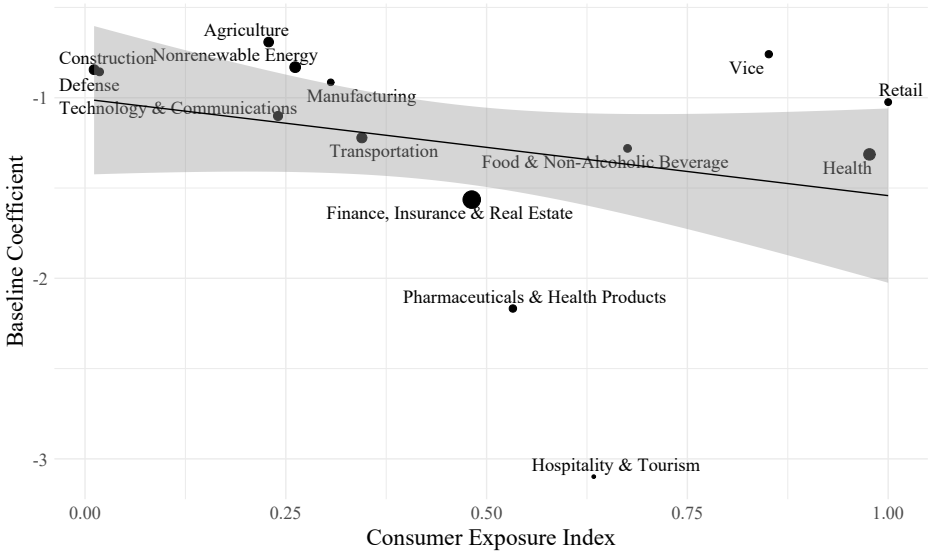
exposed to household demand may face stronger pressure to withdraw at the margin, but the underlying reputational risk is not confined to the most consumer-exposed sectors.

Table 3: Consumer Exposure Heterogeneity in the Effect of Fatal School Shootings in Competitive Districts on Republican Contributions, 2000–2024. Static PPML Model.

	Baseline	All Controls	Demographic Controls	No Controls	$100,000 Cap	$20,000 Cap
Treated	-1.164***	-1.117***	-0.638***	-0.778***	-0.754***	-0.649***
	(0.258)	(0.226)	(0.213)	(0.227)	(0.171)	(0.191)
Treated × Consumer Exposure	-0.542	-0.526	-0.316	-0.271	-0.136	0.013
	(0.568)	(0.549)	(0.481)	(0.510)	(0.404)	(0.283)
Observations	93,549	93,549	93,549	93,549	93,549	93,549
Control Mean ($)	1,336	1,336	1,336	1,336	1,336	1,336

Note: static pseudo-Poisson maximum likelihood model with district-by-industry and month-by-industry fixed effects; "Treated" is an indicator for being within 24 months of a fatal school shooting; "Treated × Consumer Exposure" interacts treatment with the industry-level BEA consumer exposure index; district-industries and month-industries with zero contributions are dropped prior to estimation; exponentiated coefficients represent multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district. Observations are weighted by total industry contributions to competitive districts. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Figure 11: Effect of Fatal School Shootings on Contributions is Larger in More Consumer-Exposed Sectors, 2000–2024.



Note: each point represents one of the fourteen industry sectors in our sample (renewable energy excluded; see text). The x-axis measures consumer exposure, defined as the ratio of personal consumption expenditures to total use of products from the 2017 BEA benchmark use table; retail trade is assigned a value of one. The y-axis shows the baseline static PPML estimate of the effect of fatal school shootings on corporate contributions to Republicans from each sector, as reported in Figure 2. Dot size reflects total contributions to competitive districts. The line shows the OLS fit weighted by total contributions to competitive districts. Standard errors are clustered by district.

C. Scope of Divestment

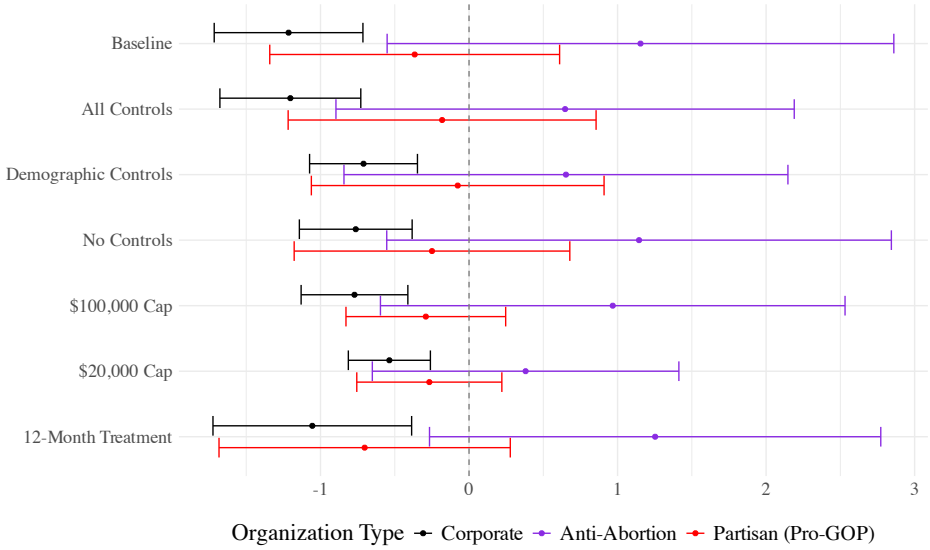
We conduct four sets of analyses to delineate the scope of our divestment finding. First, we estimate the effects of fatal school shootings on spending by non-corporate PACs. Second, we estimate the responsiveness of corporate giving to other types of shocks, including nonfatal school shootings and mass shootings. Third, we estimate the geographic scope of the effect by testing the impact of fatal school shootings on corporate PAC spending in nearby House districts. Lastly, we examine whether a similar response is found in statewide elections.

1. Corporate PACs vs. Non-Corporate PACs

We find that corporate PACs are uniquely sensitive to the shock of fatal school shootings. We estimate the impact of fatal school shootings on contributions to House Republicans by two types of non-corporate donors: multi-issue partisan Republican PACs (e.g., Americans for Prosperity Action) and anti-abortion PACs (e.g., National Right to Life). Unlike corporations, which cultivate relationships across party lines to preserve legislative access, these groups have no reputation to protect outside of their own political movement and no strategic incentive to distance themselves from Republicans following a fatal school shooting.

Anti-abortion PACs are a particularly apt placebo group: opposition to abortion rights is a defining commitment of the contemporary Republican Party, making anti-abortion organizations among the most ideologically committed donors in the Republican coalition. Like corporations, anti-abortion PACs do not have direct objectives related to guns. Moreover, as single-issue groups with a narrow policy objective, anti-abortion PACs may be less constrained by national electoral strategy than multi-issue partisan Republican PACs. Thus, anti-abortion PACs could freely divest from candidates due to potential reputational concerns if they so chose. The absence of a response among multi-issue partisan and anti-abortion PACs provides especially strong evidence that the estimated effects for corporate PACs are due to reputational risk rather than some other factor (Figure 12).

Figure 12: Effect of Fatal School Shootings on Contributions to Republicans in Competitive Districts is Unique to Corporations, 2000–2024. Static PPML Model. Anti-abortion PACs are included as a placebo.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

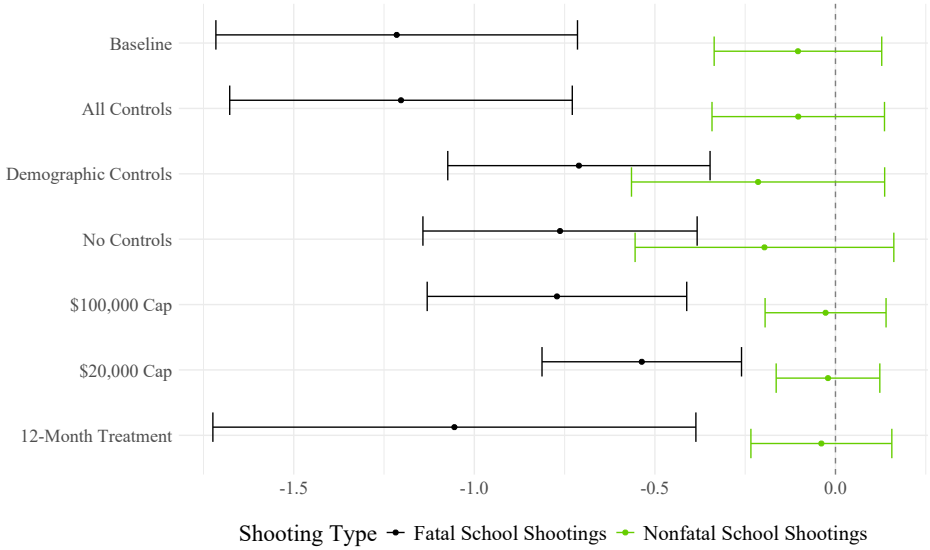
2. Differential Effects by Fatality Thresholds

The evidence indicates that corporate PACs respond selectively to only the most consequential incidents. We compare how corporate PACs respond to fatal and nonfatal school shootings in competitive districts. Whereas fatal school shootings significantly reduce corporate PAC contributions to Republican candidates, nonfatal school shootings do not generate a statistically significant response, and this sharp contrast is robust across specifications (Figure 13). This difference suggests that corporate PACs do not react to school shootings as such, but rather, they respond selectively to only the most salient incidents that potentially make continued visible political association more reputationally costly.

This fatality threshold analysis demonstrates the robustness of our main finding. The difference between a fatal and nonfatal school shooting can turn on factors as arbitrary as the precise trajectory of a bullet, making it unlikely that the two types of incidents differ

systematically in the unobserved district characteristics that could confound our estimates. Any unobservable characteristics that distinguish districts with fatal school shootings also distinguish districts with nonfatal school shootings. Thus, the null effect of nonfatal school shootings suggests that our main effect is driven by fatal school shootings themselves and not an unobserved factor correlated with them.

Figure 13: Only Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Specifications, 2000–2024. Static PPML Model.

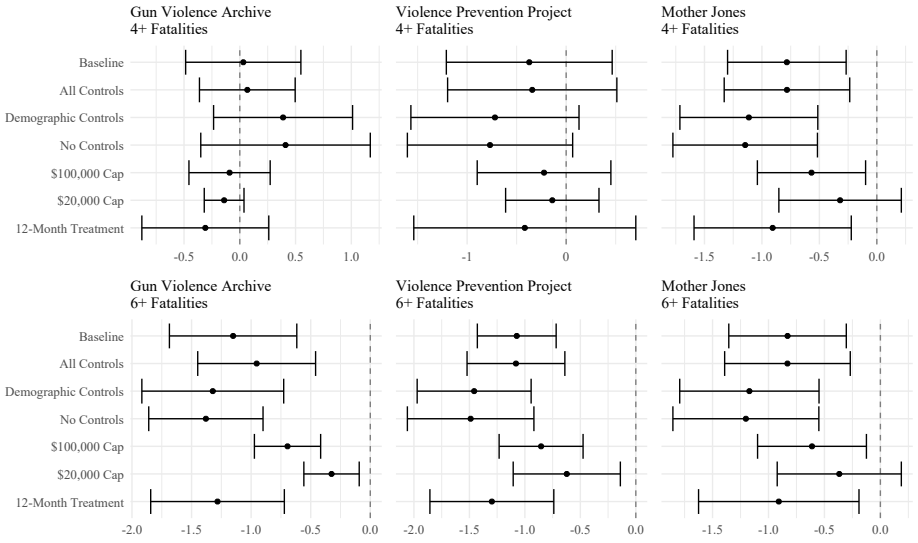


Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

We next test whether this selective response extends to mass shootings. We examine whether different levels of fatality among mass shootings elicit different responses from corporate PACs. We use fatality thresholds of four and six, mirroring thresholds used by previous literature (Booty et al. 2019; Klarevas et al. 2019). We collect mass shooting data from three sources: Mother Jones (MJ), the Gun Violence Archive (GVA), and the Violence Prevention Project (VPP) (Follman et al. 2025; Gun Violence Archive 2025; Peterson and Densley 2024). While we find no significant effect at the four-fatality threshold in competitive districts across all three datasets, at the six-fatality threshold, we find that mass shootings

significantly decrease contributions to Republicans in the affected competitive district by 68.4%, which is roughly the same as the impact of a fatal school shooting (Figure 14; baseline effect of GVA six-plus-fatality shootings $= -1.15$, $p < 0.0001$). The higher fatality threshold leaves only a single-digit number of qualifying events for each dataset, precluding strong inference. However, the directional consistency of our estimates with the school shooting results shows the robustness of our findings.[35]

Figure 14: Only High-Fatality Mass Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Specifications and Shooting Databases, 2000–2024. Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

These results are consistent with the view that corporate PACs respond selectively to consequential incidents. These responses indicate that corporate PACs retrench not in response to all violence, but only in response to shocks large enough to alter the reputational calculus of continued political support for Republicans.

35. For additional detail, see Appendix D, Subsection 7. When it comes to school shootings, high-fatality cases are rare—only ten in our sample period meet the four-fatality threshold—and we are unable to restrict the sample to competitive districts. Thus, as an alternative scope, we expand our analysis to the pooled all-district sample.

3. Geographic Spillovers

To assess whether the estimated response extends beyond the treated district and test the stable unit treatment value assumption (SUTVA), we examine geographic spillovers. We re-estimate the baseline static Poisson specification after redefining treatment so that a district-month is coded as exposed when a fatal school shooting occurred within the previous 24 months outside the district but within a specified distance of the district center, excluding districts that experienced a shooting within their own boundaries.

We implement this analysis at thresholds from 20 to 200 miles and under three alternative definitions of district center: the population centroid, the geographic centroid, and the point-on-surface.[36] Across these specifications, we find no meaningful evidence of spillover into nearby districts. To the extent that the shortest-distance estimates are modestly negative, they suggest partial treatment of the nearest neighboring districts, implying that our main estimates are, if anything, conservative.[37]

4. Impact on Statewide Elections

We investigate whether a similar response to our primary finding is present in statewide contests. We find no significant effects on contributions to Republicans in elections for U.S. senators (p-values range from 0.39 to 0.86). For U.S. governors, we find a baseline penalty on Republicans of 25.8%, but it disappears with winsorization at \$100,000 and \$20,000. Fatal school shootings do not affect contributions to Democrats in either gubernatorial or U.S. Senate races. These analyses focus on all statewide races regardless of competitiveness.[38] The absence of a decline comparable in magnitude and robustness to our baseline effect of

36. Point-on-surface is advantageous because it returns a point guaranteed to lie in the interior of the district, even in nonconvex districts. For more information on this, please see a more detailed explanation in Appendix D, Subsection 8.

37. For additional detail, see Appendix D, Subsection 8.

38. This is because the number of observations would be too low if we only include competitive races, unlike in congressional district-based analysis.

70.3% suggests that the response is strongest in the House, which is characterized by the most granular and frequent elections of any setting we analyze.[39]

Contributions to U.S. Senate candidates are made by the same federal corporate PACs examined in the main analysis. The absence of a significant estimate on Senate contributions is consistent with the logic of our primary finding. While the same federal corporate PACs that contribute to House candidates also contribute to Senate candidates, each unique Senate seat is elected every six years rather than every two, meaning that active fundraising is concentrated in a small fraction of our sample months, and the geographic diffuseness of statewide constituencies reduces the localized reputational pressure that drives our House results.

It is important to note that the statewide results are best understood as a comparative extension of our main analysis and that the gubernatorial and U.S. Senate results should be interpreted separately. Contributions to gubernatorial candidates are made by legally distinct, state-level, special interest groups operating under state-specific campaign finance laws. Therefore, a significant gubernatorial estimate, namely reduced state-level interest group contributions to Republican gubernatorial candidates, should be interpreted as a separate state-level pattern rather than as evidence about the federal corporate PACs examined in the main analysis.

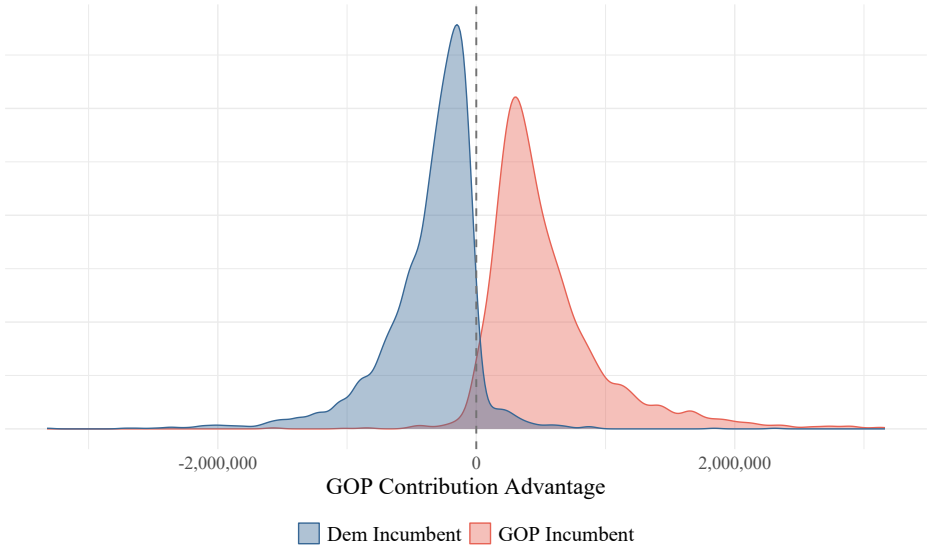
The Response is Narrowly Bounded. Taken together, these results highlight the uniqueness of our primary finding. The estimated 70.3% penalty on Republicans does not extend to non-corporate Republican-aligned PAC donors. School shootings only generate the penalty if there is at least one fatality, and mass shootings only generate a penalty if there are at least six. Effects generally do not appear outside the immediate vicinity of the shocks. This pattern is difficult to reconcile with a broader post-tragedy withdrawal in contributions to Republicans and instead points to a localized response specific to the donor class for which visible political support carries the greatest reputational risk.

39. For additional details, see Appendix D, Subsection 9.

D. Retrenchment and Electoral Outcomes

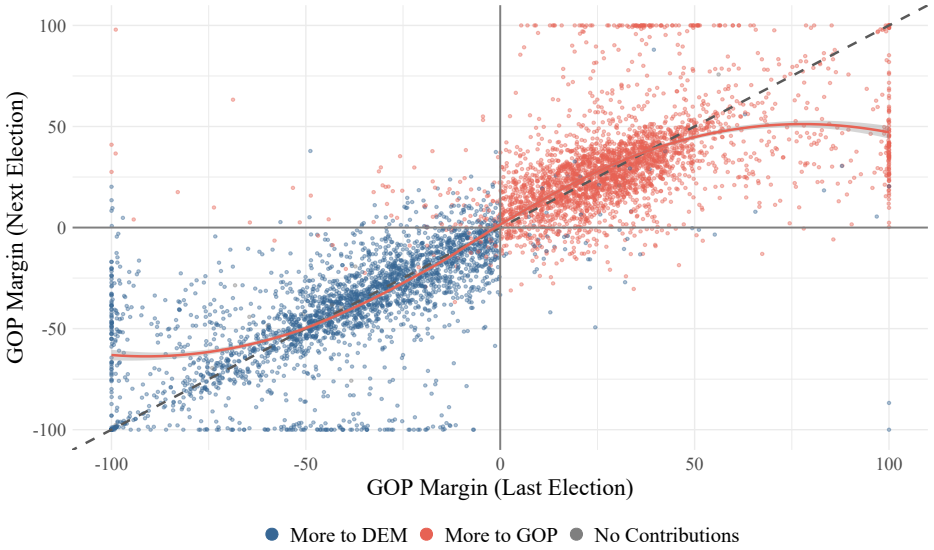
We examine whether the temporary withdrawal in visible corporate support is accompanied by durable partisan reordering in the next election. While the financial response from corporate donors is large, the electoral implications appear limited because district partisanship is too stable for a temporary nine-month funding dip to overcome. District-level partisan outcomes are persistent across elections. Corporate PAC contribution advantages are shown to have a clear bimodal distribution: the incumbent almost always possesses a fundraising advantage (Figure 15). Moreover, Republican vote margin in the next election cycle closely tracks Republican vote margin in the last cycle, with most observations clustered near the 45-degree line (Figure 16). Electoral movement is concentrated near the center, where competitive districts can plausibly change hands, but large partisan reversals are uncommon. The broader electoral environment is therefore one of continuity rather than realignment.

Figure 15: Republican Candidates' Corporate PAC Contribution Advantage by Party Incumbency, 2000–2024.



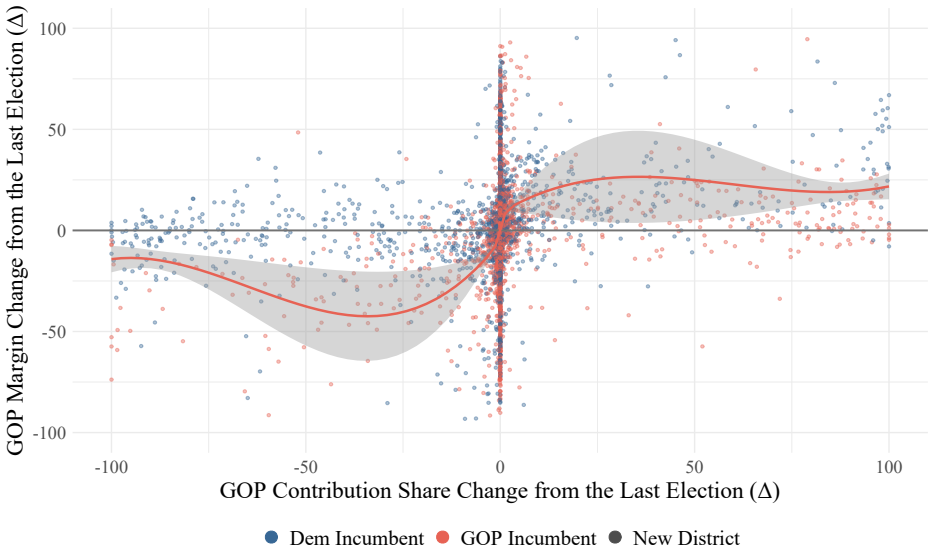
Note: y-axis represents density; positive values in the horizontal axis shows the gap of corporate PAC contributions received by candidates in each party.

Figure 16: Electoral Persistence Across Election Cycles, 2000–2024.



Note: plot of Republican margin in the next election against Republican margin in the last election at the district-cycle level. Positive values indicate Republican victories. The dashed line denotes equality of margins across cycles; the solid curve is a nonparametric fit.

Figure 17: Change in Republican Vote Margin and Change in Republican PAC Contribution Share, 2000–2024.



Note: plot of the change in Republican vote margin from the last election against the change in the Republican share of sector PAC contributions at the district-cycle level. Positive values indicate movement toward Republicans. The solid curve is a nonparametric fit.

Even sizable shifts in the partisan allocation of PAC support are not systematically associated with subsequent changes in vote margin (Figure 17). This points to a similar pattern: electoral outcomes are stable across cycles and not driven by corporate PAC behavior. Much of the mass is concentrated near zero on the x-axis, showing that durable changes to corporate PAC behavior across cycles are rare. Thus, contribution adjustments of the magnitude we document in our main findings are unlikely to produce changes in electoral outcomes.

V. Conclusion

Political contributions serve two functions that standard accounts of corporate political spending treat as one: they secure legislative access and they publicly signal a firm's political ties. This paper shows that when fatal school shootings and mass shootings concentrate public scrutiny on gun policy, firms delicately balance both functions, temporarily withdrawing from the reputationally risky channel of political spending while preserving the long-term financial relationships that secure access.

The pattern of selective and transient divestment we find is consistent with that account. Corporate PAC contributions to Republican House candidates fall sharply by 70% after fatal school shootings in competitive districts and by 61% in safe Democratic districts, where continued visible association is costly and the strategic return to maintaining support is comparatively low. The penalty is absent in safe Republican districts, where the expected value of access is higher and warrants continued support. Contributions do not shift toward Democrats and return to pre-shooting levels within nine months, leaving the overall, long-term investment of corporate PAC money unchanged. The selective and transient character of the observed divestment tracks the calculus of reputational exposure and strategic return rather than indicating that firms have a general aversion to Republican, pro-gun candidates.

The transient character of the divestment has important implications for the incentives facing candidates. Candidates who maintain pro-gun positions bear a financial penalty. However, this penalty proves short-lived: contributions recover in short order, and electoral outcomes in affected districts remain unchanged. Candidates who anticipate that corporate PAC contributions will return face no incentive to revise their pro-gun policy positions.

That logic helps explain a pressing public policy puzzle: gun violence is the single largest cause of death among American children, among the leading causes of death for adults, and a severe public health crisis in the United States. Yet repeated tragedies have not produced federal legislative intervention. Our findings show why shocks fail to generate lasting policy change. When the standard incentive for behavioral change, namely a sustained shift in the payoffs to a given action, is absent, shocks produce temporary retreat rather than lasting realignment. So long as those underlying incentives remain intact, the policy status quo is likely to endure.

While our data do not allow us to make claims about what individuals believe in the wake of fatal school shootings or the deadliest mass shootings, the corporate behavior that we have uncovered provides a basis for some inference about what corporate PACs appear to anticipate in the aftermath of such gun tragedies. Corporate PACs are profit-maximizing actors that do not, presumably, alter politically consequential giving decisions without some expectation that doing so serves their interests. If withdrawing support from a Republican candidate entails a cost, such as forgone access, goodwill, or future favor, firms should incur that cost only when continued visible support is expected to carry an offsetting reputational risk. The pattern we document is therefore consistent with an implicit model of firms anticipating a temporary increase in local scrutiny of Republican candidates after salient gun violence shocks, especially where the political value of continued support is low or where the visibility of association is high.

The localized and short-lived nature of the response supports a second inference. If firms believed that a shooting signaled a durable, broad shift in public opinion against the

Republican position on gun policy, they would have reason to reduce support for Republicans nationally, including in adjacent and safe districts, rather than only in the affected district for roughly nine months. We observe no such spillover. Instead, the withdrawal is concentrated in the affected House district, appears only in particular electoral contexts, and dissipates within roughly nine months. The absence of a broader retreat suggests that corporate PACs treat these shocks as ephemeral and emotionally driven, rather than as evidence of a sustained realignment of views on gun policy. Once the salience of a given tragedy fades, the access value of Republican ties again dominates the reputational cost of maintaining them.

This interpretation also clarifies why the contribution response has limited implications for policy change. The financial penalty imposed by corporate PACs is large but temporary. It is not redirected toward Democratic candidates, does not extend broadly across electoral geography, and is not accompanied by durable electoral realignment. Candidates therefore have little reason to interpret the corporate withdrawal as a sustained change in the political returns to their gun policy positions.

The contrast with gun lobby PACs underscores why this temporary corporate withdrawal does not necessarily change the incentives sustaining the status quo. While corporate PACs withdraw financial support from Republican House candidates after fatal school shootings, gun policy PACs move in the opposite direction. Baldwin et al. (2026) show that pro-gun PACs increase support for Republican candidates over a similar post-shooting period. We cannot determine whether gun lobby PACs respond independently to the same shootings or instead perceive corporate withdrawal and increase support because their preferred candidates have become more financially exposed. In either case, the opposing responses are substantively important. Corporate PACs temporarily reduce visible support when reputational risk rises, while gun lobby PACs increase support when the gun policy stakes become salient. Rather than producing a durable shift in the incentives facing Republican candidates, the dual response helps preserve the underlying policy equilibrium.

Although here we study gun policy, the behavior we document reflects a general feature of disclosed corporate political spending. A firm's disclosed political ties carry a reputational cost that rises with public attention and an access value that is unaffected by it. When an event raises the reputational cost, firms withdraw visible support for as long as attention stays elevated, because the value of the tie itself is unchanged. Durable change in corporate political behavior would require a shock that erodes that access value, and fatal school shootings and high-fatality mass shootings do not. They make support for pro-gun candidates briefly costly and leave its long-term value intact, so corporate money returns to its prior course once attention fades. The same pattern should arise wherever firms hold disclosed political ties that a salient event can suddenly expose, leaving the underlying behavior, and the policies it helps sustain, unchanged once attention moves on.

Disclosures

Institutional Review Board Status

The Stanford University Institutional Review Board has determined that this study does not involve human subjects as defined in 45 CFR 46.102(e) and therefore does not require full review by the Institutional Review Board. This determination was made on April 03, 2026.

Data Availability

This project uses six primary data components: (1) contribution data obtained from OpenSecrets (OpenSecrets 2025), (2) fatal school shooting data from the K-12 School Shooting Database (Riedman 2025), (3) mass shooting data from the Mother Jones, Gun Violence Archive, and Violence Prevention Project databases (Follman et al. 2025; Gun Violence Archive 2025; Peterson and Densley 2024), (4) ACS microdata and the 2000 Census obtained from IPUMS (Ruggles et al. 2025), (5) House election results (Leip 2025), and (6) publicly available geographic and economic data (Bureau of Economic Analysis 2023; Bureau of Labor Statistics 2025; Lewis et al. 2017; Missouri Census Data Center 2000, 2014, 2018, 2022; Walker 2025). The merged analytic panel, replication code, and the handcoded crosswalk mapping OpenSecrets donor categories to industry sector codes will be made available upon publication.

References

Ansolabehere, Stephen, John M. de Figueiredo, and James M. Snyder Jr. 2003. "Why Is There So Little Money in U.S. Politics?" *Journal of Economic Perspectives* 17 (1): 105–130.

Baldwin, Eric A., Takuma Iwasaki, and John J. Donohue. 2026. "School Shootings and the Strategic Contributions of Gun Policy PACs in US House Elections." *Proceedings of the National Academy of Sciences* 123 (9): e2514343123.

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

Booty, Marisa, Jayne O'Dwyer, Daniel Webster, Alex McCourt, and Cassandra Crifasi. 2019. "Describing a "Mass Shooting": The Role of Databases in Understanding Burden." *Injury Epidemiology* 6 (1): 47.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2024. "Revisiting Event-Study Designs: Robust and Efficient Estimation." *The Review of Economic Studies* 91 (6): 3253–3285.

Bureau of Economic Analysis. 2023. *Detailed Input-Output Use Table (Supply-Use Framework), 2017 Benchmark.* [dataset]. U.S. Department of Commerce.

Bureau of Labor Statistics. 2025. *Consumer Price Index for All Urban Consumers.*

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller. 2008. "Bootstrap-Based Improvements for Inference with Clustered Errors." *Review of Economics and Statistics* 90 (3): 414–427.

CDC. 2026. *Underlying Cause of Death Database.*

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. "The Effect of Minimum Wages on Low-Wage Jobs." *The Quarterly Journal of Economics* 134 (3): 1405–1454.

Chen, Jiafeng, and Jonathan Roth. 2024. "Logs with Zeros? Some Problems and Solutions." *The Quarterly Journal of Economics* 139 (2): 891–936.

Fingerhut, Hannah. 2024. *Students Rally at the Iowa Capitol Days After Perry School Shooting.* Associated Press.

Fisman, Raymond. 2001. "Estimating the Value of Political Connections." *American Economic Review* 91 (4): 1095–1102.

Follman, Mark, Gavin Aronsen, and Deanna Pan. 2025. *U.S. Mass Shooters, 1982–2023.* Accessed February 1, 2025.

Goldstick, Jason E., Rebecca M. Cunningham, and Patrick M. Carter. 2022. "Current Causes of Death in Children and Adolescents in the United States." *New England Journal of Medicine* 386 (20): 1955–1956.

Goodman-Bacon, Andrew. 2021. "Difference-in-Differences with Variation in Treatment Timing." *Journal of Econometrics* 225 (2): 254–77.

Grinshteyn, Erin, and David Hemenway. 2016. "Violent Death Rates: The US Compared with Other High-Income OECD Countries, 2010." *American Journal of Medicine* 129 (3): 266–273.

Grossman, Gene M., and Elhanan Helpman. 1994. "Protection for Sale." *American Economic Review* 84 (4): 833–850.

Gun Violence Archive. 2025. *Gun Violence Archive.* [dataset].

Hassan, Tarek A, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun. 2019. "Firm-Level Political Risk: Measurement and Effects." *The Quarterly Journal of Economics* 134 (4): 2135–2202.

Hong, Harrison, and Marcin Kacperczyk. 2009. "The Price of Sin: The Effects of Social Norms on Markets." *Journal of Financial Economics* 93 (1): 15–36.

Hornik, Kurt. 2005. "A CLUE for CLUster Ensembles." *Journal of Statistical Software* 14 (12).

Jayachandran, Seema. 2006. "The Jeffords Effect." *Journal of Law and Economics* 49 (2): 397–425.

Klarevas, Louis, Andrew Conner, and David Hemenway. 2019. "The Effect of Large-Capacity Magazine Bans on High-Fatality Mass Shootings, 1990–2017." *American Journal of Public Health* 109 (12): 1754–1761.

Kline, Patrick, and Andres Santos. 2012. "A Score Based Approach to Wild Bootstrap Inference." *Journal of Econometric Methods* 1 (1): 23–41.

Kroszner, Randall S., and Thomas Stratmann. 1998. "Interest-Group Competition and the Organization of Congress: Theory and Evidence from Financial Services' Political Action Committees." *American Economic Review* 88 (5): 1163–1187.

Leip, David. 2025. *Dave Leip's Atlas of U.S. Presidential Elections.*

Lewis, Jeffrey B., Brandon DeVine, Lincoln Pitcher, and Kenneth C. Martis. 2017. *Digital Boundary Definitions of United States Congressional Districts, 1789–2017.* Data file and codebook. Accessed March 15, 2025. https://cdmaps.polisci.ucla.edu.

Liu, Licheng, Ye Wang, and Yiqing Xu. 2024. "A Practical Guide to Counterfactual Estimators for Causal Inference with Time-Series Cross-Sectional Data." *American Journal of Political Science* 68 (1): 160–76.

Mady, Khalid, Mohamed Salaheldeen, Hashim Refaat, and Mohamed Battour. 2025. "The Impact of Social Media on Consumer Boycotts: Mediating Roles of Animosity, Behavioral Control, and Efficacy." *Social Sciences & Humanities Open* 12:102041.

Missouri Census Data Center. 2000. *Geocorr 2000.* [dataset].

Missouri Census Data Center. 2014. *Geocorr 2014.* [dataset].

Missouri Census Data Center. 2018. *Geocorr 2018.* [dataset].

Missouri Census Data Center. 2022. *Geocorr 2022.* [dataset].

OpenSecrets. 2025. "Full Universe of Interest Group and PAC Donations, Federal and State." [unpublished dataset].

Papadimitriou, Christos H., and Kenneth Steiglitz. 1982. *Combinatorial Optimization: Algorithms and Complexity.* USA: Prentice-Hall, Inc.

Pebesma, Edzer. 2018. "Simple Features for R: Standardized Support for Spatial Vector Data." *The R Journal* 10 (1): 439–446.

Persakis, Antonios, Theodoros Nikolopoulos, Ioannis C Negkakis, and Athanasios Pavlopoulos. 2025. "Greenwashing in Marketing: A Systematic Literature Review and Bibliometric Analysis." *International Review on Public and Nonprofit Marketing* 22 (4): 957–992.

Peterson, Jillian K., and James A. Densley. 2024. *Violence Project Database of Mass Shootings in the United States.* [dataset]. Retrieved March 1, 2025.

Reny, Tyler T., Benjamin J. Newman, John B. Holbein, and Hans J. G. Hassell. 2023. "Public Mass Shootings Cause Large Surges in Americans' Engagement with Gun Policy." *PNAS Nexus* 2 (12).

Riedman, David. 2025. *K-12 School Shooting Database.* [dataset].

Roemer, Tobias. 2023. "School Shootings Increase NRA Donations." *Science Advances* 9 (eadi7545): 1–8.

Ruggles, Steven, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. 2025. *IPUMS USA: Version 16.0.*

Santos Silva, João M. C., and Silvana Tenreyro. 2006. "The Log of Gravity." *The Review of Economics and Statistics,* 641–658.

Snyder, James M. 1990. "Campaign Contributions as Investments: The U.S. House of Representatives, 1980-1986." *Journal of Political Economy* 98 (6): 1195–1227.

Walker, Kyle. 2025. *Tigris: Load Census TIGER/Line Shapefiles.* R package version 2.2.1.

Supporting Information – Table of Contents

Appendix A. Panel Construction A1
1. Redistricting Crosswalk A1
2. Campaign Contributions A2
3. School Shootings A2
4. Demographic Covariates A3
5. Election-Related Covariates A3
6. Consumer Exposure Index A3

Appendix B. Main Descriptive Statistics B1

Appendix C. Additional Descriptive Statistics C1
1. Alternate Subsamples C1
2. Corporate Contributions C3
3. Largest Corporate PACs in Sample C5

Appendix D. Additional Robustness Results D1
1. Contributions to Republicans D1
2. Contributions to Democrats D6
3. Log-Linear Specification D13
4. Staggered Treatment Estimators D25
5. Direct Expenditures Only D31
6. Leave-One-Out D35
7. Alternative Shooting Types D37
8. Geographic Spillover D48
9. Spillover to Statewide Elections D52

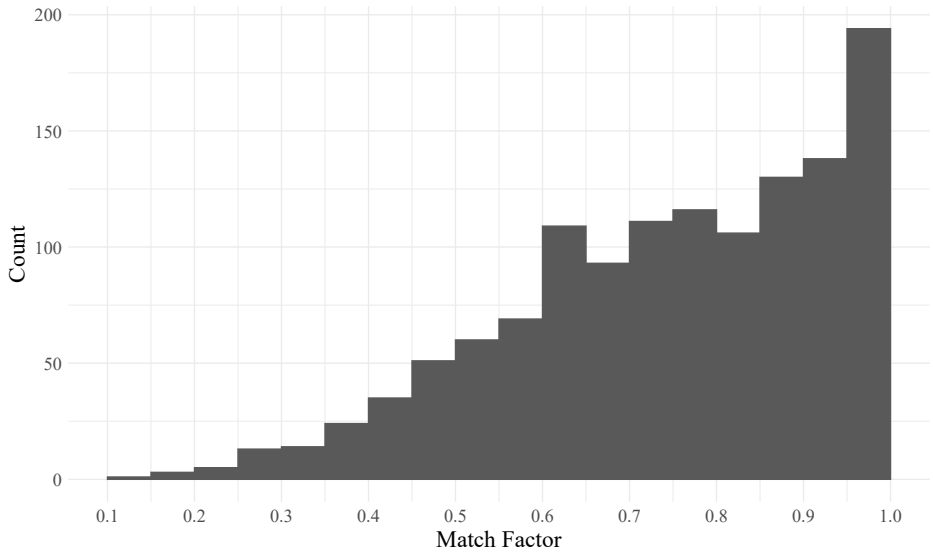
Appendix A — Panel Construction

1. Redistricting Crosswalk

The redistricting crosswalk is built using geographic correspondence data that measures the population overlap between old and new district boundaries (Missouri Census Data Center 2000, 2014, 2018, 2022). We use two matching algorithms depending on whether a state's seat number increased, decreased, or remained constant across cycles. For states that maintained a constant number of seats, we use the Hungarian algorithm, which finds the globally optimal one-to-one matching between old and new districts that maximizes total geographic overlap (Papadimitriou and Steiglitz 1982). We implement the Hungarian algorithm using the `clue` package in R (Hornik 2005). For states that gained or lost seats, we use a greedy algorithm that iteratively locks in the highest-overlap match available. Matched districts are assigned the same `district_id`, and districts with no predecessor (newly created districts) or successor (eliminated seats) are assigned `district_id`'s not linked to the other decade, reflecting that no meaningful geographic continuity exists across the redistricting boundary. California, which gained a 53rd seat in 2000 and lost it in 2020, is handled separately using the appropriate algorithm for each cycle.

As shown in Figure A1, match quality is high: the median match factor across all matched pairs exceeds 0.75, meaning the typical matched district pair shares more than three-quarters of each district's population. The small number of weak matches that do occur are in states that underwent substantial redistricting, where no high-overlap match is geometrically possible.

Figure A1: High Geographic Overlap Between Matched Districts Across the 2000, 2010, and 2020 Redistricting Cycles.



2. Campaign Contributions

Data on campaign contributions comes from OpenSecrets (2025), which includes both direct and independent expenditures. We include both direct contributions and independent expenditures, aggregated to the district-month level. For direct contributions, we assign each dollar to the party of the recipient candidate. For independent expenditures, we assign dollars based on whether the expenditure supports or opposes a candidate: expenditures supporting a Republican candidate or opposing a Democratic candidate are coded as Republican, and vice versa. We restrict the sample to contributions made to or on behalf of Democratic and Republican candidates, with two exceptions: Bernard Sanders is coded as a Democrat throughout his time in the House and Virgil Goode is coded as a Republican during the period in which he ran as an independent. Both coding decisions reflect caucus affiliations. All other third-party and independent candidates are excluded. To follow the next-election convention, campaign contributions are mapped to the district each candidate is seeking to represent, even if the candidate is currently representing a different district. For example, Eric Swalwell represented California's 14th district until 2023 and has represented the 15th district since 2023; contributions to Swalwell would thus be mapped to the 15th district starting after the 2020 election.

Occasionally, candidates run for a district and receive contributions, but the district is later abolished in redistricting and the candidate drops out. These contributions cannot be mapped to any district according to our next-election convention, but they are quite rare: of over 1.63 million corporate contributions in our sample period, just 309 went to candidates who sought election in districts that were later abolished in redistricting.

When money is returned by the candidate to the donor, this is reflected as a negative contribution in the OpenSecrets data. To ensure all contribution amounts are positive, all negative contribution amounts are replaced with zeroes after aggregation to the district-month level. Negative amounts are replaced with zeroes after aggregation so that returns occurring in the same district-month as a positive contribution net out before the floor is applied, rather than being discarded entirely at the contribution level. For the total industry sector contribution variables, the floor is imposed after summing across sectors, so that returns in one sector can offset positive contributions in another before the floor is applied. A $500 contribution from an agriculture PAC and a $250 return from a defense PAC in the same district-month would yield a total of $250, rather than $500 if the return had been floored at zero before aggregation. This is unlikely to drive the results, as just 2.7% of the contributions we use have negative contribution amounts.

3. School Shootings

School shooting data comes from Riedman (2025). Shootings are geocoded to congressional districts using the latitude and longitude coordinates in the Riedman database and congressional district shapefiles. For the 101st through 114th Congress, shapefiles are sourced from Lewis et al. (2017). For the 115th through 119th Congress, shapefiles are sourced from Walker (2025).

4. Demographic Covariates

Demographic controls are constructed from American Community Survey (ACS) microdata and the 2000 Census, obtained from IPUMS. We construct district-year measures of educational attainment, median household income, racial composition, and unemployment for each congressional district from 2000 through 2024.

Because ACS respondents are identified by Public Use Microdata Area (PUMA) rather than congressional district, we use geographic correspondence crosswalks to probabilistically assign each individual to a congressional district (Missouri Census Data Center 2000, 2014, 2018, 2022). When a PUMA spans multiple districts, each respondent is assigned to a district with probability proportional to the share of the PUMA's population residing in that district. District assignments for covariates follow the next-election boundary convention described in the main text. Since ACS data are reported at the calendar year level, we align with the convention by shifting December observations forward by one year, so that December of year t is assigned the ACS values for year $t + 1$.

For 2006-2024, we use annual ACS data directly, matching each survey year to the congressional boundaries in effect under the next-election convention. The 2000-2005 period requires additional treatment: we crosswalk both the 2000 Census and the 2006 ACS to the post-2002 district boundaries and linearly interpolate all demographic variables for the intervening years. Median household income is adjusted for inflation using the Consumer Price Index, normalized to the CPI base period (1982-1984) (Bureau of Labor Statistics 2025).

5. Election-Related Covariates

Election-related variables in our panel include the margin of the last House election and an indicator for Democratic victory in the last House election (Leip 2025). Independent victories are coded according to caucus affiliations: Bernard Sanders's victories in Vermont are coded as Democratic victories, Virgil Goode's 2000 victory is coded as a Republican victory, and Jo Ann Emerson's 1996 victory is coded as a Republican victory. Election results for prior cycles are matched to district-months using the `district_id` variable, ensuring that election outcomes are correctly attributed even when district boundaries change across redistricting cycles. As districts with no matched predecessor have no electoral history under their `district_id`, they are excluded from any analysis that uses election-related variables to filter the sample or as covariates. As just 792 of the 130,500 district-months in our sample (0.61%) corresponded to newly created districts with no matched predecessor, this exclusion is unlikely to be meaningful.

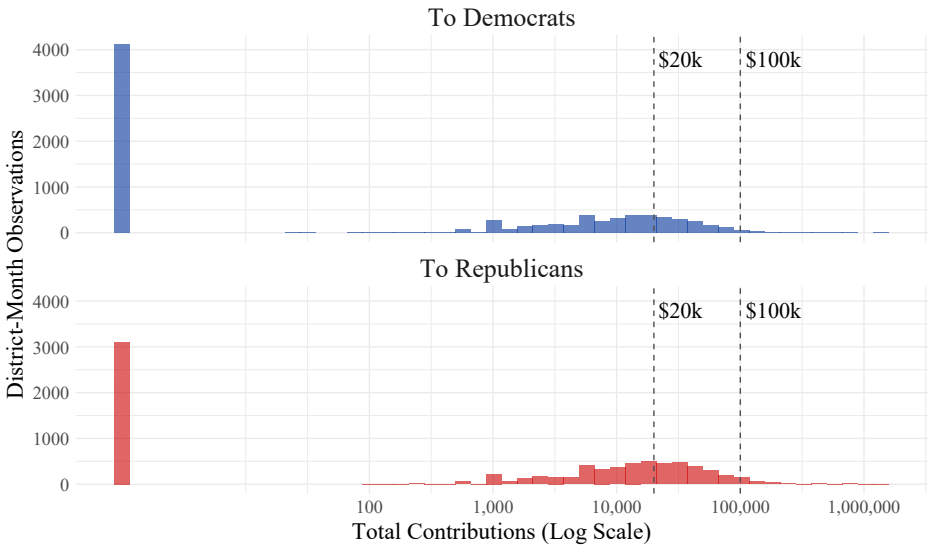
6. Consumer Exposure Index

The consumer exposure index was calculated using the 2017 detailed BEA benchmark use table (Bureau of Economic Analysis 2023). For each sector, consumer exposure is defined as the ratio of personal consumption expenditures to total use of products, both drawn from the BEA detail-level use table (columns F01000 and T019 respectively). Detail-level BEA

industry categories are aggregated to our sector codes via a handcoded crosswalk. For each of our codes, personal consumption and total use were summed across detail-level industry categories, then divided. Retail trade was manually assigned a consumer exposure of one, since the BEA records retail output as trade margins rather than commodity production. Renewable energy is not identified at the BEA detail level, so no consumer exposure index was calculated for the sector.

Appendix B — Main Descriptive Statistics

Figure B1: Distribution of Total Corporate Contribution Amounts Across Competitive District-Months, 2000–2024.



Note: district-months with zero contributions are plotted at 1, since log(0) is undefined.

Figure B2: Percent of Contributions in Competitive Districts to Democrats by Industry Sector, 2002–2024 Election Cycles.

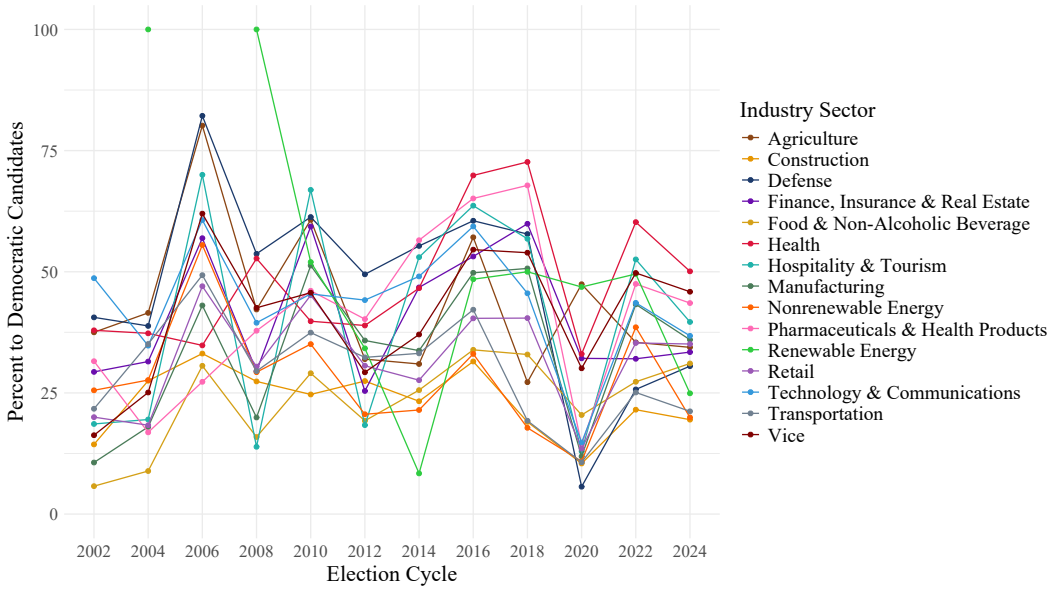


Figure B3: Percent of Competitive Districts with At Least One Contribution by Industry Sector, 2002–2024 Election Cycles.

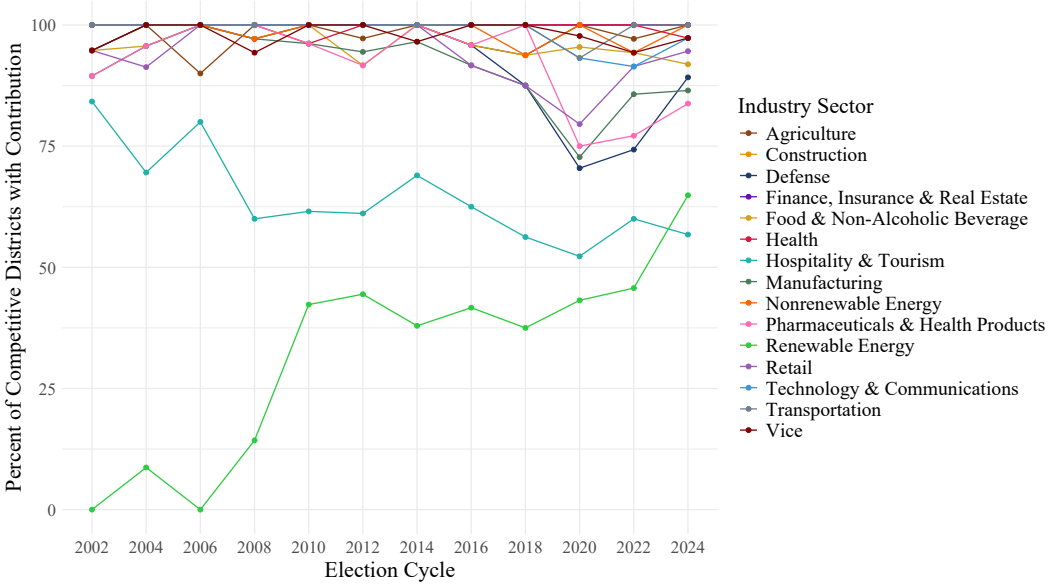


Figure B4: Total Contributions by Month of Cycle and Interest Group Type, 2002–2024 Election Cycles.



Note: x-axis runs from December two years before election year to November of election year. Contributions are distributed throughout cycle, with clustering near elections.

Figure B5: Treatment Status of Competitive Districts (Main Sample, Last Election Margin Within 5%), 2000–2024.

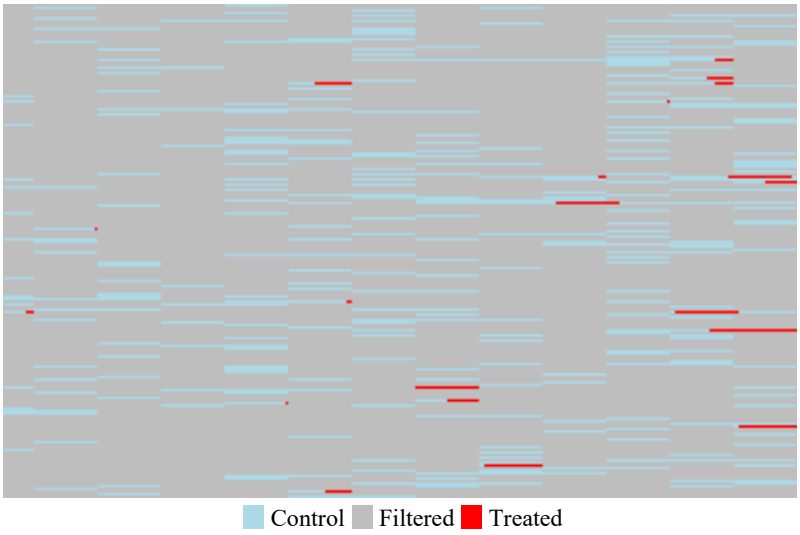


Figure B6: Treatment Status of Competitive Districts (Last Election Margin Within 10%), 2000–2024.

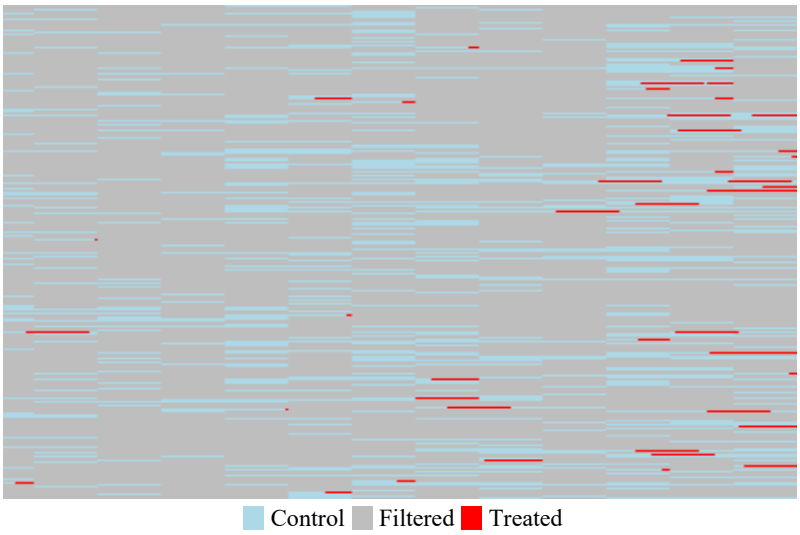


Table B1: Balance Test: Competitive Districts With vs. Without Shootings

	Shooting in Past 24 Months		No Shooting in Past 24 Months	
Variable	Mean	St. Dev.	Mean	St. Dev.
Dem. Victory Last Election	0.551	0.498	0.528	0.499
Margin of Last Election	2.756	1.489	2.510	1.435
Median Income (1982-1984 Dollars)	24,324	4,114	26,043	6,064
Unemployment	6.241	3.041	6.192	2.380
Percent Bachelors or More	31.492	8.611	31.385	9.621
Percent Black	9.252	5.907	8.536	8.384
Percent White	64.319	18.919	75.415	15.419
Observations	256		7,964	

Note: Sample is competitive district-months. Compares district-months that had a fatal school shooting within the past 24 months to those that did not.

Table B2: Sector Consumer Exposure Index

Sector	Consumer Exposure Index
Retail	1.000
Health	0.977
Vice	0.851
Food & Non-Alcoholic Beverage	0.675
Hospitality & Tourism	0.633
Pharmaceuticals & Health Products	0.533
Finance, Insurance & Real Estate	0.482
Transportation	0.345
Manufacturing	0.306
Nonrenewable Energy	0.262
Technology & Communications	0.240
Agriculture	0.229
Defense	0.018
Construction	0.011

Note: consumer exposure index is computed from the 2017 BEA Use Table. For all industries except retail, the index equals personal consumption expenditure divided by total use. Retail is set to one by construction.

Appendix C — Additional Descriptive Statistics

1. Alternate Subsamples

Figure C1: Treatment Status of Safe Democratic Districts (Last Election Margin Over 5%), 2000–2024.

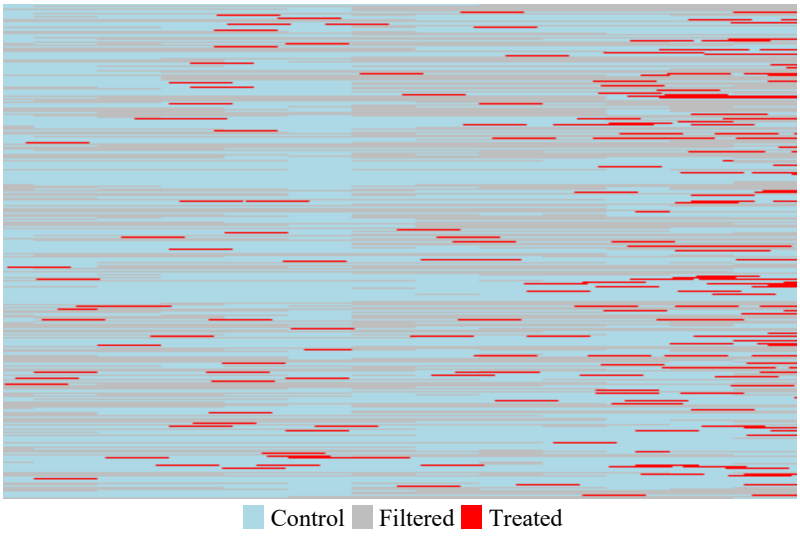


Figure C2: Treatment Status of Safe Democratic Districts (Last Election Margin Over 10%), 2000–2024.

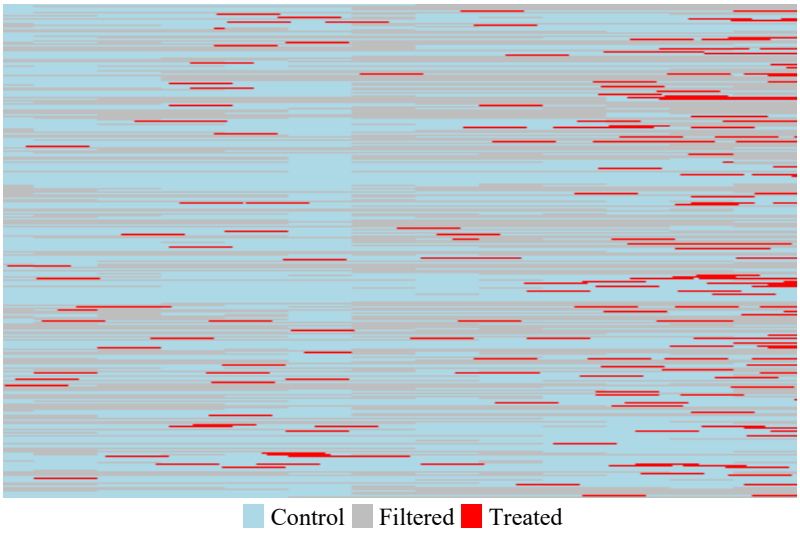


Figure C3: Treatment Status of Safe Republican Districts (Last Election Margin Over 5%), 2000–2024.

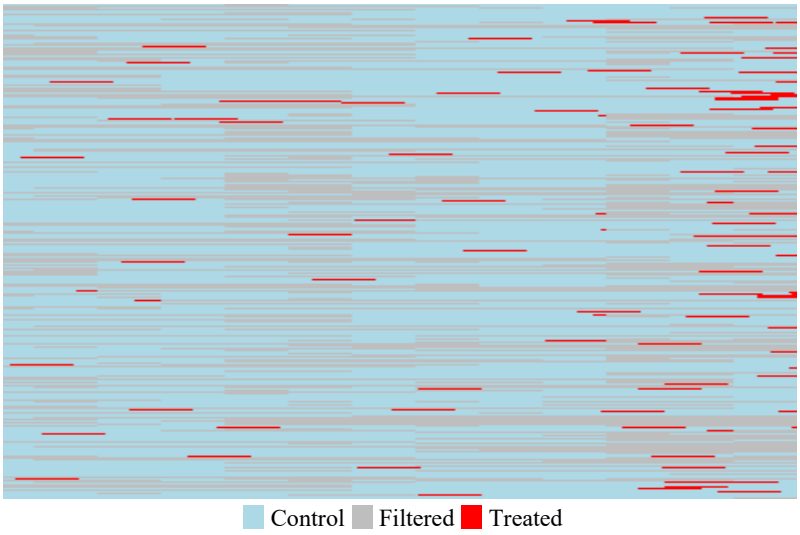
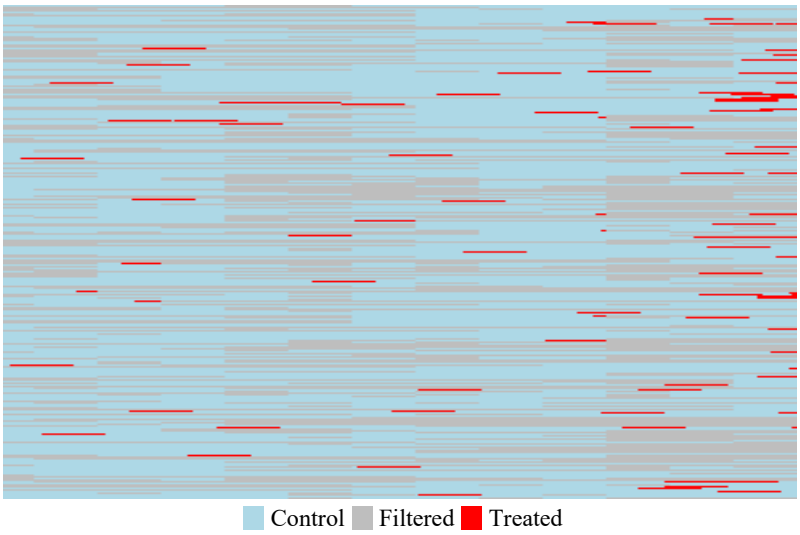


Figure C4: Treatment Status of Safe Republican Districts (Last Election Margin Over 10%), 2000–2024.



2. Corporate Contribution Patterns

Figure C5: Total Contributions to Competitive Districts by Industry Sector, 2002–2024 Election Cycles.

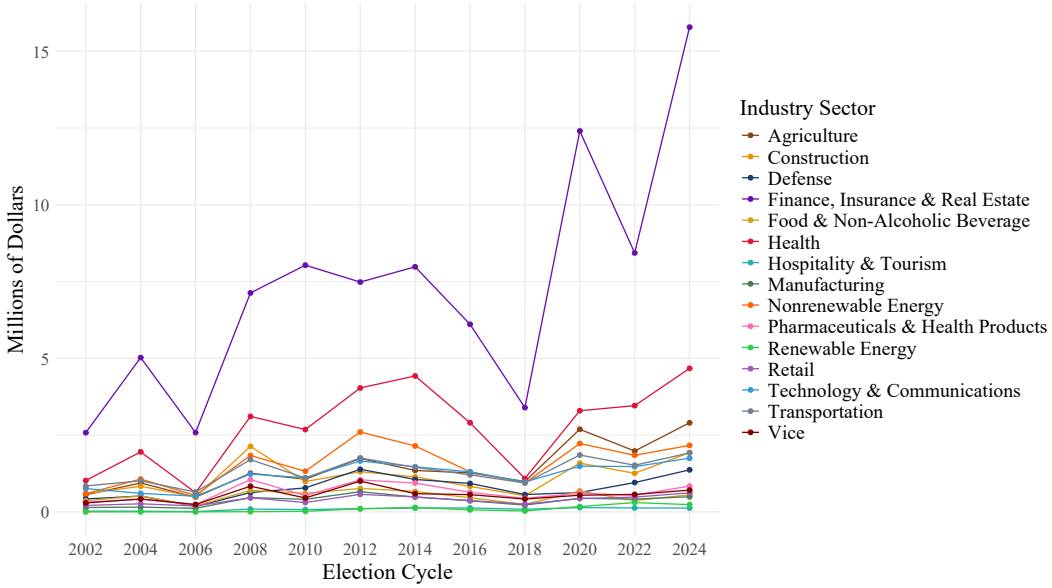


Figure C6: Total Contributions by Industry Sector, 2002–2024 Election Cycles.

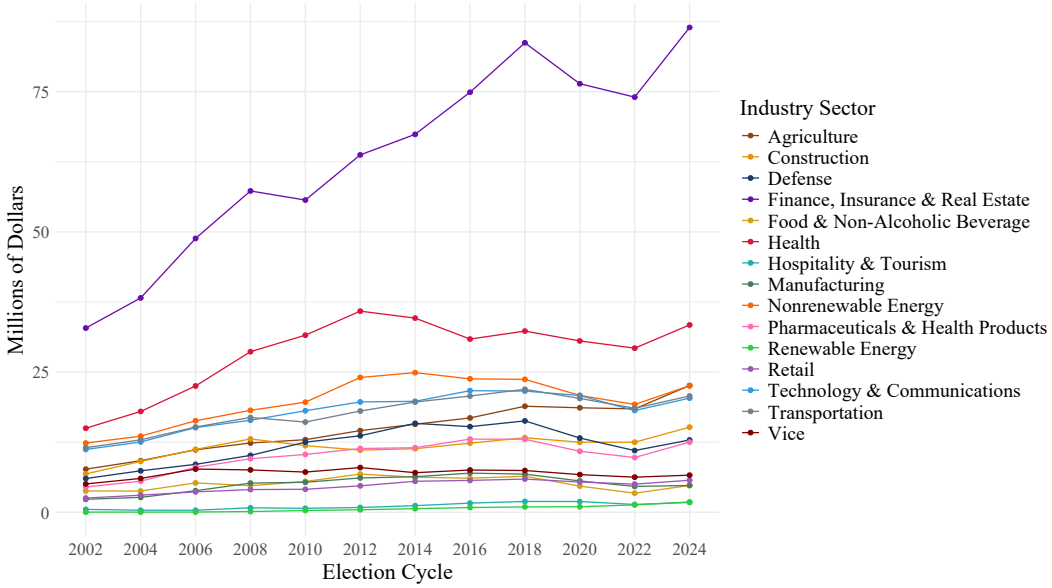


Figure C7: Percent of Contributions to Democrats by Industry Sector, 2002–2024 Election Cycles.

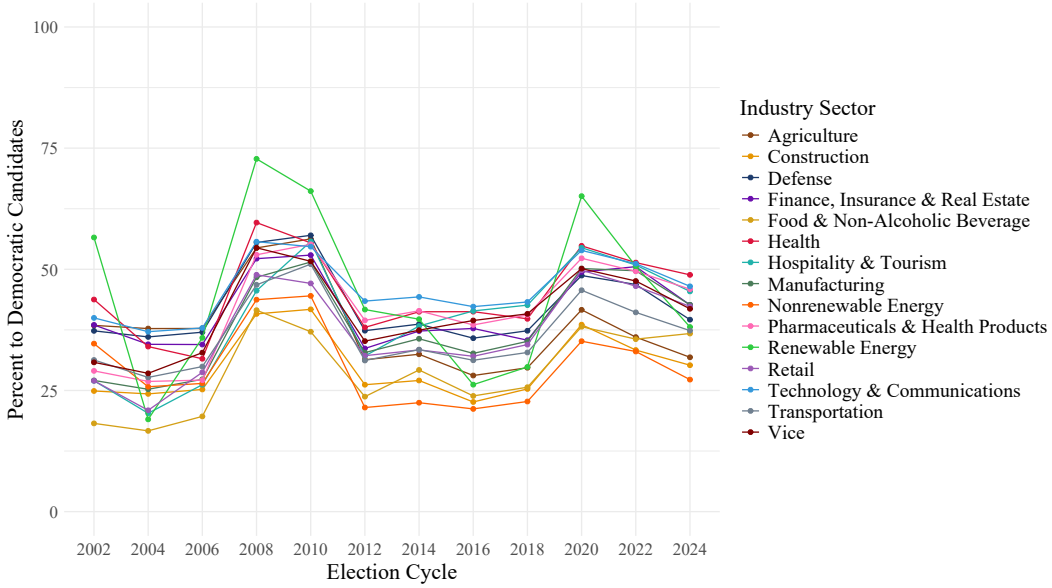
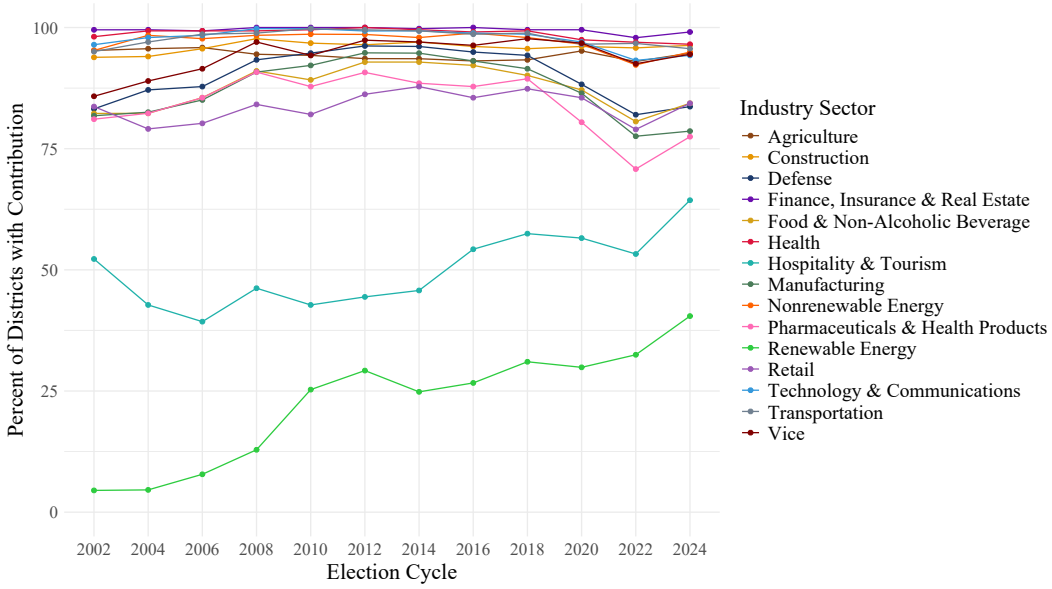


Figure C8: Percent of Districts with At Least One Contribution by Industry Sector, 2002–2024 Election Cycles.



3. Largest Corporate PACs in Sample

Agriculture:

- American Crystal Sugar
- Farm Credit Council
- Dairy Farmers of America
- National Cattlemen's Assn
- Deere & Co

Construction:

- National Assn of Home Builders
- Associated Builders & Contractors
- American Consulting Engineers Council
- Associated General Contractors
- National Electrical Contractors Assn

Defense:

- Lockheed Martin
- Raytheon Co
- Northrop Corp
- Boeing Co
- United Technologies

Nonrenewable Energy:

- National Rural Electric Cooperative Assn
- Koch Inc
- Exxon Corp
- Chevron Corp
- Valero Energy

Finance, Insurance & Real Estate:

- National Assn of Realtors
- National Assn of Realtors Congressional Fund
- America's Credit Unions
- American Bankers Assn
- National Assn of Insurance & Financial Advisors

Food & Non-Alcoholic Beverage:

- National Restaurant Assn
- Bloomin' Brands
- McDonald's Corp

- FMI The Food Industry Assn
- Coca-Cola Co

Health:

- American Medical Assn
- American Hospital Assn
- American Dental Assn
- American Society of Anesthesiologists
- American Assn of Orthopaedic Surgeons

Hospitality & Tourism:

- American Hotel & Lodging Assn
- US Travel Assn
- Asian American Hotel Owners Assn
- Marriott International
- American Society of Travel Advisors

Manufacturing:

- Honeywell International
- General Electric
- International Paper
- Nucor Corp
- Procter & Gamble

Pharmaceuticals & Health Products:

- Pfizer Inc
- Amgen Inc
- GSK plc
- Eli Lilly & Co
- Merck & Co

Renewable Energy:

- Poet LLC
- Growth Energy
- American Wind Energy Assn
- Solar Energy Industries Assn
- American Clean Power Assn

Retail:

- Home Depot
- Wal-Mart Stores

- National Assn of Convenience Stores
- International Council of Shopping Centers
- Lowe's Companies

Technology & Communications:

- AT&T Inc
- Comcast Corp
- Bell Atlantic
- NCTA The Internet & Television Assn
- National Assn of Broadcasters

Transportation:

- National Auto Dealers Assn
- United Parcel Service
- FDX Corp
- Union Pacific Corp
- BNSF Railway

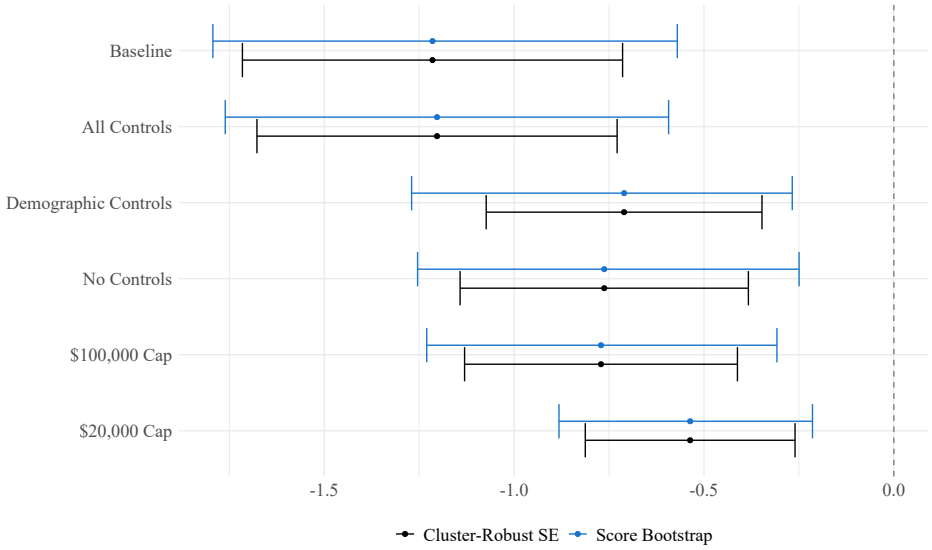
Vice:

- National Beer Wholesalers Assn
- Altria Group
- Wine & Spirits Wholesalers of America
- RJ Reynolds Tobacco
- Anheuser-Busch

Appendix D — Additional Robustness Results

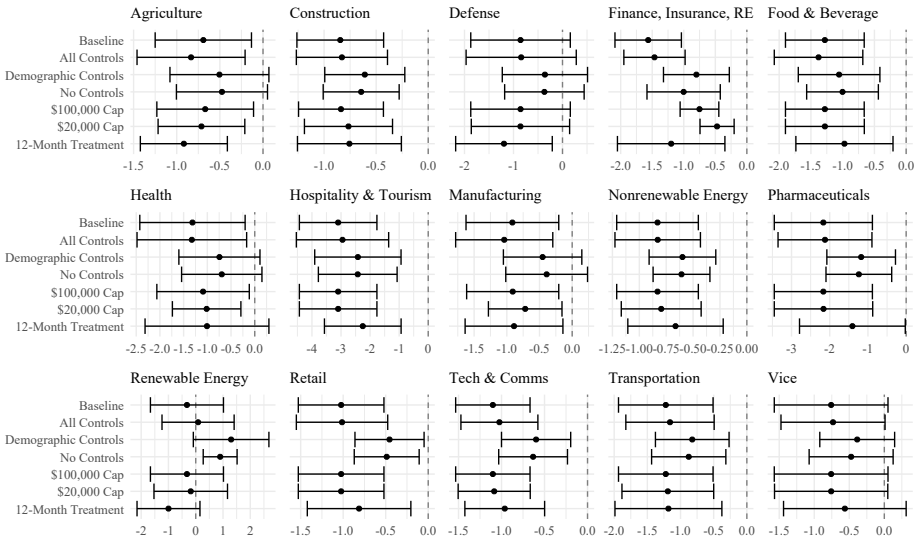
1. Contributions to Republicans

Figure D1: Main Result Remains Significant with Score Bootstrapping, 2000–2024. Static PPML Model.



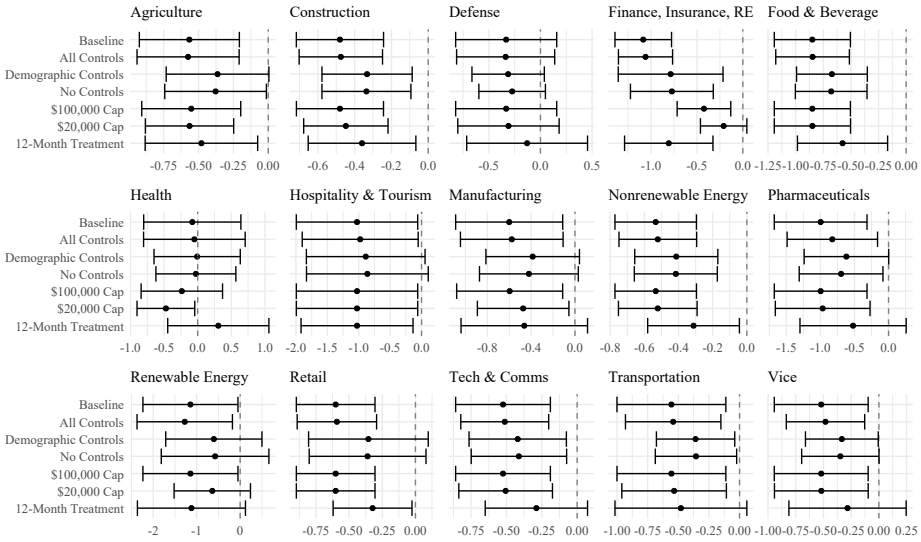
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Blue confidence intervals are computed via score bootstrapping with Rademacher weights, clustered at the district level. Black confidence intervals are derived from standard errors clustered by district.

Figure D2: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Sectors and Specifications, 2000–2024. Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D3: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Sectors and Specifications, 2000–2024 (10% Competitiveness Threshold). Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Table D1: Effect of Fatal School Shootings in Competitive Districts on Contributions to Republicans Across Sectors, 2000–2024. Static PPML Model.

	All Corporate	Agriculture	Construction	Defense	Finance, Ins. & Real Estate	Food & Beverage	Health	Hospitality & Tourism	Manuf.	Nonrenewable Energy	Pharma & Health	Renewable Energy	Retail	Tech & Comms	Transport	Vice
Baseline	-1.215***	-0.692**	-0.845***	-0.857*	-1.564***	-1.281***	-1.314**	-3.099***	-0.915**	-0.831***	-2.167***	-0.322	-1.024***	-1.101***	-1.222***	-0.759*
	(0.255)	(0.285)	(0.212)	(0.518)	(0.269)	(0.316)	(0.567)	(0.680)	(0.362)	(0.194)	(0.655)	(0.683)	(0.257)	(0.221)	(0.364)	(0.414)
All Controls	-1.203***	-0.834***	-0.829***	-0.843	-1.464***	-1.380***	-1.327**	-2.949***	-1.040***	-0.829***	-2.124***	0.086	-1.014***	-1.025***	-1.159***	-0.732*
	(0.242)	(0.320)	(0.223)	(0.574)	(0.248)	(0.356)	(0.590)	(0.810)	(0.379)	(0.203)	(0.627)	(0.674)	(0.274)	(0.228)	(0.340)	(0.379)
Demographic Controls	-0.710***	-0.505*	-0.609***	-0.359	-0.800***	-1.056***	-0.745*	-2.420***	-0.452	-0.599***	-1.177**	1.297*	-0.455**	-0.598***	-0.823***	-0.387
	(0.185)	(0.293)	(0.196)	(0.444)	(0.266)	(0.328)	(0.436)	(0.758)	(0.306)	(0.158)	(0.458)	(0.707)	(0.207)	(0.205)	(0.283)	(0.272)
No Controls	-0.763***	-0.476*	-0.644***	-0.370	-1.002***	-1.002***	-0.696	-2.425***	-0.391	-0.608***	-1.238***	0.895***	-0.488**	-0.633***	-0.876***	-0.474
	(0.194)	(0.269)	(0.186)	(0.414)	(0.296)	(0.288)	(0.432)	(0.691)	(0.319)	(0.135)	(0.439)	(0.317)	(0.195)	(0.204)	(0.286)	(0.306)
$100,000 Cap	-0.771***	-0.670**	-0.838***	-0.857*	-0.751***	-1.281***	-1.090**	-3.099***	-0.910**	-0.831***	-2.167***	-0.322	-1.024***	-1.101***	-1.222***	-0.759*
	(0.183)	(0.286)	(0.208)	(0.518)	(0.156)	(0.316)	(0.498)	(0.680)	(0.359)	(0.194)	(0.655)	(0.683)	(0.257)	(0.221)	(0.364)	(0.414)
$20,000 Cap	-0.536***	-0.714***	-0.766***	-0.858*	-0.472***	-1.280***	-1.015***	-3.099***	-0.719**	-0.796***	-2.163***	-0.183	-1.024***	-1.085***	-1.191***	-0.759*
	(0.141)	(0.256)	(0.216)	(0.512)	(0.138)	(0.317)	(0.369)	(0.680)	(0.287)	(0.189)	(0.657)	(0.688)	(0.257)	(0.214)	(0.353)	(0.412)
12-Month Treatment	-1.055***	-0.918***	-0.757***	-1.195**	-1.200***	-0.972**	-1.008	-2.252***	-0.890**	-0.663***	-1.407**	-0.998*	-0.813***	-0.963***	-1.182***	-0.563
	(0.341)	(0.257)	(0.255)	(0.503)	(0.435)	(0.390)	(0.667)	(0.673)	(0.382)	(0.226)	(0.706)	(0.588)	(0.311)	(0.237)	(0.411)	(0.446)
Observations	8,004	7,285	7,687	6,092	7,788	6,918	7,485	2,830	6,387	7,559	6,531	1,389	6,035	7,114	7,478	6,360
Control Mean ($)	18,784	1,234	1,323	652	6,626	621	2,123	82	365	1,738	542	74	401	1,050	1,442	509

Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table D2: Effect of Fatal School Shootings in Competitive Districts on Contributions to Republicans Across Sectors, 2000–2024 (10% Competitiveness Threshold). Static PPML Model.

	All Corporate	Agriculture	Construction	Defense	Finance, Ins. & Real Estate	Food & Beverage	Health	Hospitality & Tourism	Manuf.	Nonrenewable Energy	Pharma & Health	Renewable Energy	Retail	Tech & Comms	Transport	Vice
Baseline	-0.649***	-0.566***	-0.480***	-0.332	-1.084***	-0.849***	-0.080	-1.028**	-0.601**	-0.534***	-0.996***	-1.144**	-0.601***	-0.524***	-0.556**	-0.520**
	(0.139)	(0.183)	(0.121)	(0.250)	(0.157)	(0.176)	(0.369)	(0.493)	(0.249)	(0.122)	(0.347)	(0.558)	(0.151)	(0.171)	(0.227)	(0.216)
All Controls	-0.642***	-0.575***	-0.475***	-0.337	-1.060***	-0.847***	-0.049	-0.977**	-0.577**	-0.521***	-0.825**	-1.275**	-0.592***	-0.512***	-0.542***	-0.482***
	(0.123)	(0.187)	(0.116)	(0.243)	(0.150)	(0.170)	(0.386)	(0.471)	(0.239)	(0.116)	(0.339)	(0.560)	(0.153)	(0.159)	(0.199)	(0.180)
Demographic Controls	-0.475***	-0.364*	-0.333***	-0.313*	-0.786***	-0.672***	-0.008	-0.889*	-0.386*	-0.413***	-0.618*	-0.605	-0.355	-0.420**	-0.359**	-0.334**
	(0.143)	(0.188)	(0.125)	(0.179)	(0.291)	(0.163)	(0.328)	(0.482)	(0.218)	(0.124)	(0.316)	(0.565)	(0.230)	(0.176)	(0.163)	(0.167)
No Controls	-0.470***	-0.378**	-0.336***	-0.274*	-0.773***	-0.678***	-0.027	-0.863*	-0.421*	-0.416***	-0.696**	-0.577	-0.361	-0.412**	-0.355**	-0.348*
	(0.130)	(0.186)	(0.123)	(0.165)	(0.230)	(0.165)	(0.304)	(0.495)	(0.230)	(0.124)	(0.314)	(0.632)	(0.225)	(0.172)	(0.169)	(0.178)
$100,000 Cap	-0.400***	-0.552***	-0.480***	-0.332	-0.423***	-0.849***	-0.236	-1.028**	-0.596**	-0.534***	-0.996***	-1.144**	-0.601***	-0.524***	-0.556**	-0.520**
	(0.107)	(0.181)	(0.121)	(0.250)	(0.149)	(0.176)	(0.309)	(0.493)	(0.247)	(0.122)	(0.347)	(0.558)	(0.151)	(0.171)	(0.227)	(0.216)
$20,000 Cap	-0.301***	-0.565***	-0.448***	-0.310	-0.209	-0.848***	-0.473**	-1.028**	-0.473**	-0.522***	-0.966***	-0.641	-0.601***	-0.506***	-0.534**	-0.519**
	(0.094)	(0.162)	(0.117)	(0.250)	(0.129)	(0.176)	(0.219)	(0.493)	(0.213)	(0.118)	(0.354)	(0.448)	(0.151)	(0.169)	(0.218)	(0.216)
12-Month Treatment	-0.408**	-0.480**	-0.360**	-0.129	-0.807***	-0.576***	0.307	-1.027**	-0.463	-0.312**	-0.521	-1.121*	-0.323**	-0.288	-0.479*	-0.283
	(0.192)	(0.206)	(0.149)	(0.299)	(0.246)	(0.208)	(0.384)	(0.455)	(0.295)	(0.137)	(0.397)	(0.634)	(0.152)	(0.185)	(0.275)	(0.270)
Observations	16,260	15,457	15,834	14,289	15,888	14,815	15,198	8,415	14,123	15,687	14,060	3,489	13,626	15,007	15,556	14,426
Control Mean ($)	16,900	1,066	1,144	630	5,961	547	1,913	75	348	1,539	503	60	368	989	1,291	465

Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table D3: Effect of Fatal School Shootings in Competitive Districts on Contributions to Republicans, 2000–2024. Static Stacked PPML Model.

	All Corporate	Agriculture	Construction	Defense	Finance, Ins. & Real Estate	Food & Beverage	Health	Hospitality & Tourism	Manuf.	Nonrenewable Energy	Pharma & Health	Renewable Energy	Retail	Tech & Comms	Transport	Vice
Baseline	-0.814***	-0.518*	-0.620***	-0.736***	-1.188***	-0.723*	-0.577	-2.236***	-0.730***	-0.613**	-0.627	-1.295	-0.615*	-0.568**	-0.678***	0.189
	(0.252)	(0.299)	(0.227)	(0.184)	(0.379)	(0.436)	(0.647)	(0.551)	(0.228)	(0.243)	(0.484)	(0.790)	(0.333)	(0.288)	(0.238)	(0.295)
Demographic Controls	-0.780***	-0.437	-0.578***	-0.682***	-1.335***	-0.641	-0.172	-1.624**	-0.540*	-0.539**	-0.535	-1.328*	-0.549*	-0.532*	-0.685***	0.348
	(0.263)	(0.316)	(0.220)	(0.195)	(0.444)	(0.462)	(0.668)	(0.668)	(0.311)	(0.234)	(0.491)	(0.733)	(0.334)	(0.283)	(0.245)	(0.317)
$100,000 Cap	-0.525**	-0.483	-0.620***	-0.736***	-0.654**	-0.723*	-0.442	-2.236***	-0.730***	-0.613**	-0.627	-1.295	-0.615*	-0.568**	-0.678***	0.189
	(0.211)	(0.307)	(0.227)	(0.184)	(0.282)	(0.436)	(0.647)	(0.551)	(0.228)	(0.243)	(0.484)	(0.790)	(0.333)	(0.288)	(0.238)	(0.295)
$20,000 Cap	-0.447***	-0.437	-0.553**	-0.748***	-0.370*	-0.719	-0.536	-2.236***	-0.730***	-0.618**	-0.624	-1.295	-0.615*	-0.585**	-0.693***	0.189
	(0.165)	(0.298)	(0.232)	(0.179)	(0.215)	(0.438)	(0.516)	(0.551)	(0.228)	(0.242)	(0.479)	(0.790)	(0.333)	(0.268)	(0.238)	(0.295)
Observations	12,684	10,014	11,274	7,428	11,869	8,911	10,079	2,480	6,976	10,814	7,617	1,729	7,394	8,942	10,707	7,681
Control Mean ($)	19,868	1,811	1,552	1,308	7,992	765	2,755	420	637	1,980	797	894	666	1,555	1,743	722

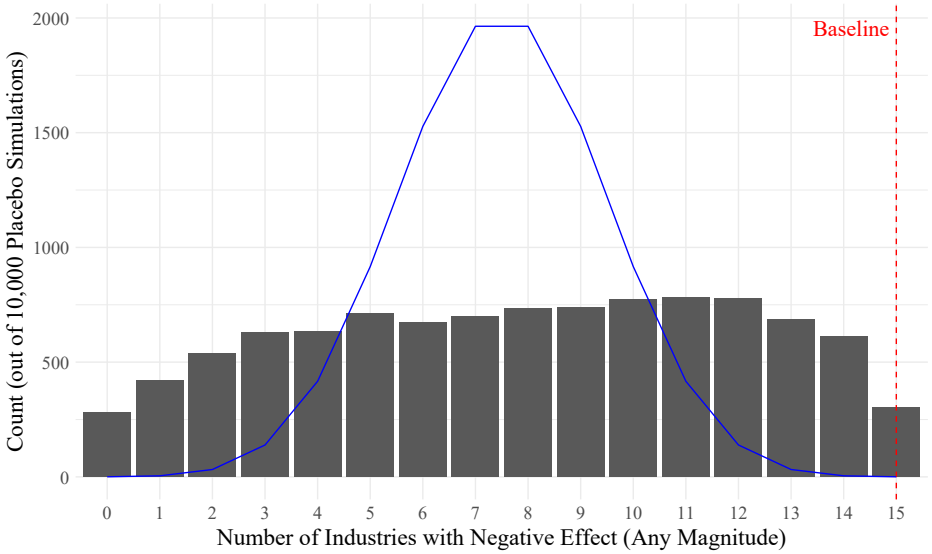
Note: static stacked pseudo-Poisson maximum likelihood difference-in-differences model; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; within each stack, districts and months with zero contributions in all observations are excluded prior to estimation. The treatment period runs from each shooting month to the end of the election cycle. Standard errors clustered by district in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table D4: Effect of Fatal School Shootings on Contributions to Republicans by District Competitiveness, 2000–2024. Static PPML Model.

	Competitive (Within 5%)	Competitive (Within 10%)	Safe D (Over 5%)	Safe D (Over 10%)	Safe R (Over 5%)	Safe R (Over 10%)
Baseline	-1.215***	-0.649***	-0.688**	-0.940***	0.020	0.056
	(0.255)	(0.139)	(0.272)	(0.308)	(0.082)	(0.088)
All Controls	-1.203***	-0.642***	-0.398	-0.373	0.021	0.055
	(0.242)	(0.123)	(0.287)	(0.344)	(0.080)	(0.087)
Demographic Controls	-0.710***	-0.475***	-0.401	-0.385	0.022	0.056
	(0.185)	(0.143)	(0.287)	(0.346)	(0.080)	(0.086)
No Controls	-0.763***	-0.470***	-0.684**	-0.957***	0.021	0.058
	(0.194)	(0.130)	(0.272)	(0.306)	(0.082)	(0.088)
$100,000 Cap	-0.771***	-0.400***	-0.685**	-0.928***	0.030	0.054
	(0.183)	(0.107)	(0.281)	(0.313)	(0.069)	(0.073)
$20,000 Cap	-0.536***	-0.301***	-0.482*	-0.590**	0.011	0.033
	(0.141)	(0.094)	(0.268)	(0.272)	(0.038)	(0.038)
12-Month Treatment	-1.055***	-0.408**	-0.779***	-1.169***	0.010	0.015
	(0.341)	(0.192)	(0.298)	(0.452)	(0.073)	(0.079)
Observations	8,004	16,260	51,433	46,149	62,304	57,816
Control Mean ($)	18,784	16,900	830	651	22,984	22,821

Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Figure D4: Number of Negative Industry Sector Effects Exceeds 96.96% of Placebo Runs, 2000–2024. Static PPML Model.



Note: gray bars show distribution of the number of sectors with negative placebo effects on contributions to Republicans (regardless of statistical significance level); blue line shows expected distribution assuming uncorrelated sector contributions; red line shows baseline number of significant negative sector effects.

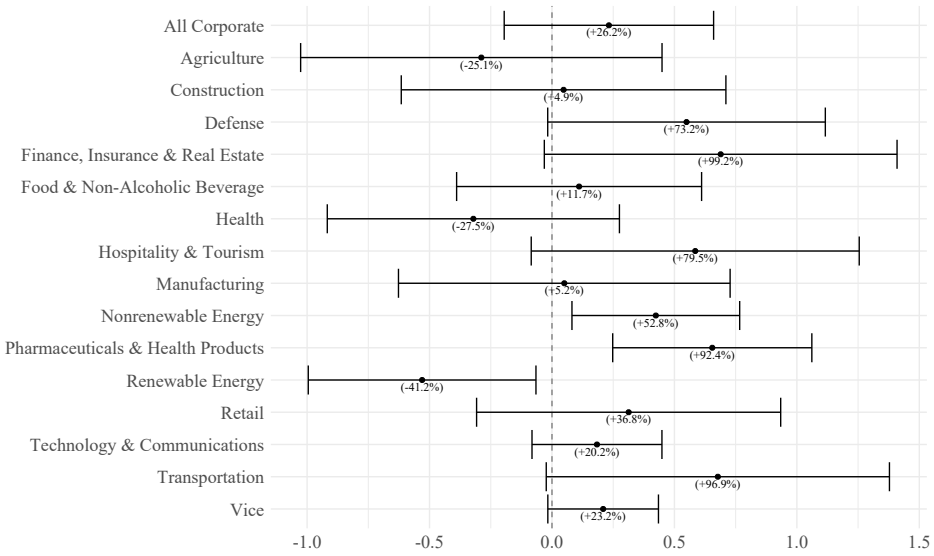
Table D5: Consumer Exposure Heterogeneity in the Effect of Fatal School Shootings in Competitive Districts on Republican Contributions, 2000–2024. Static PPML Model. (Unweighted)

	Baseline	All Controls	Demographic Controls	No Controls	$100,000 Cap	$20,000 Cap
Treated	-0.986***	-0.977***	-0.597***	-0.654***	-0.828***	-0.778***
	(0.249)	(0.237)	(0.189)	(0.197)	(0.211)	(0.229)
Treated × Consumer Exposure	-0.513	-0.504	-0.272	-0.256	-0.199	-0.147
	(0.445)	(0.444)	(0.391)	(0.401)	(0.359)	(0.276)
Observations	93,549	93,549	93,549	93,549	93,549	93,549
Control Mean ($)	1,336	1,336	1,336	1,336	1,336	1,336

Note: static pseudo-Poisson maximum likelihood model with district-by-industry and month-by-industry fixed effects; "Treated" is an indicator for being within 24 months of a fatal school shooting; "Treated × Consumer Exposure" interacts treatment with the industry-level BEA consumer exposure index; district-industries and month-industries with zero contributions are dropped prior to estimation; exponentiated coefficients represent multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district. Unlike main consumer exposure table, observations are all given equal weight. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

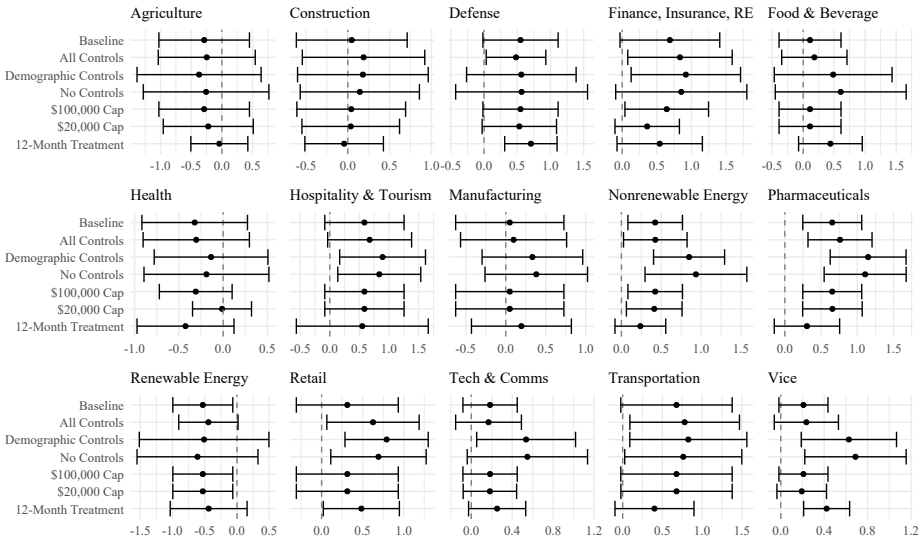
2. Contributions to Democrats

Figure D5: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts Across Sectors, 2000–2024. Static PPML Model.



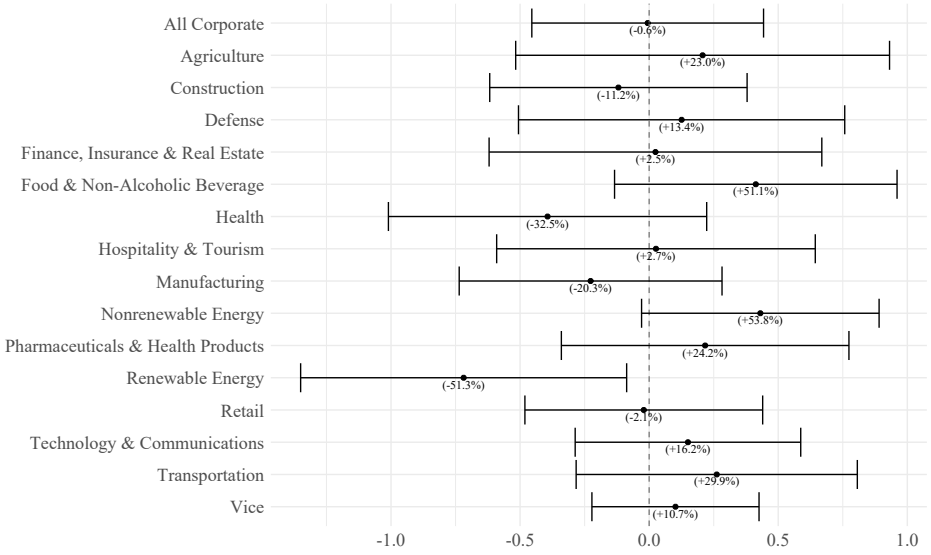
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D6: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts Across Sectors and Specifications, 2000–2024. Static PPML Model.



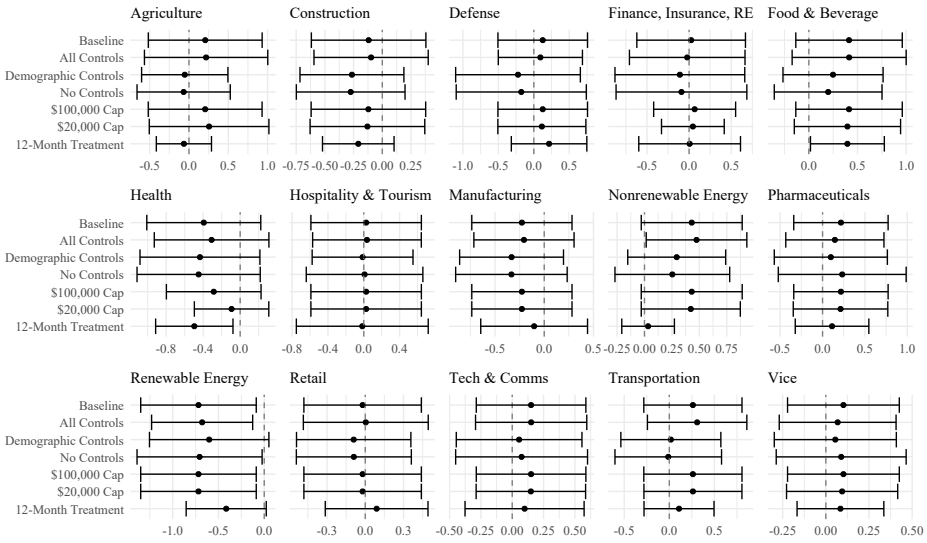
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D7: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts Across Sectors (10% Competitiveness Threshold), 2000–2024. Static PPML Model.



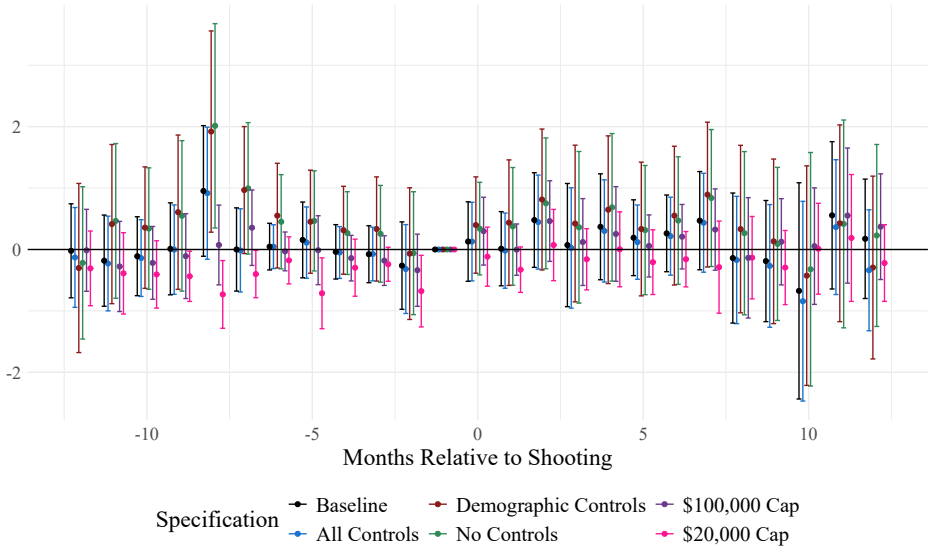
Note: static pseudo-Poisson maximum likelihood mode with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D8: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts Across Sectors and Specifications (10% Competitiveness Threshold), 2000–2024. Static PPML Model.



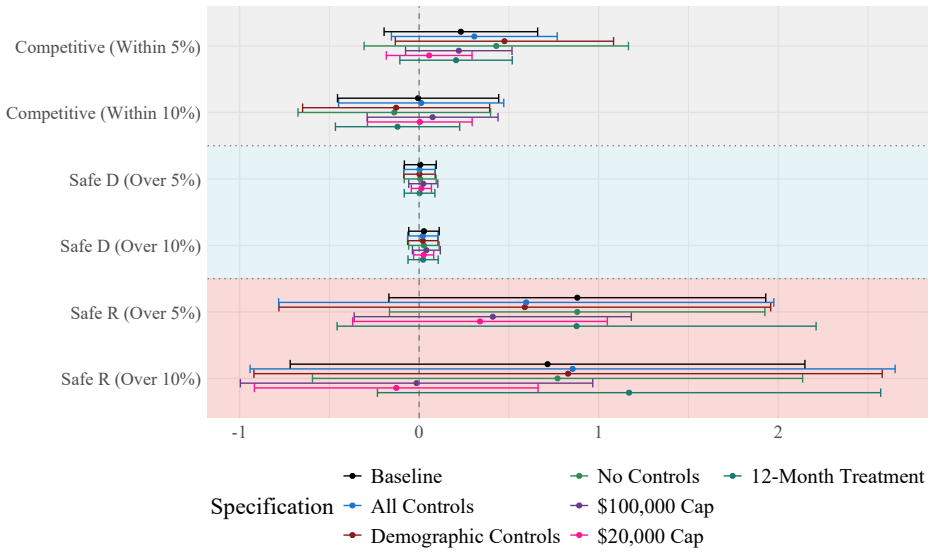
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D9: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts, 2000–2024. Dynamic PPML Model.



Note: dynamic Poisson model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D10: Fatal School Shootings Do Not Affect Contributions to Democrats Across District Types, 2000–2024. Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Table D6: Effect of Fatal School Shootings in Competitive Districts on Contributions to Democrats Across 15 Sectors, 2000–2024. Static Stacked PPML Model.

	Baseline	Demographic Controls	$100,000 Cap	$20,000 Cap
Fatal School Shootings	-0.174	-0.212	0.034	0.148
	(0.211)	(0.235)	(0.186)	(0.151)
Observations	10,872	10,872	10,872	10,872
Control Mean ($)	14,520	14,520	14,520	14,520

Note: static stacked pseudo-Poisson maximum likelihood difference-in-differences model; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; within each stack, districts and months with zero contributions in all observations are excluded prior to estimation. The treatment period runs from each shooting month to the end of the election cycle. Standard errors clustered by district in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table D7: Effect of Fatal School Shootings in Competitive Districts on Contributions to Democrats Across Sectors, 2000–2024. Static PPML Model.

	All Corporate	Agriculture	Construction	Defense	Finance, Ins. & Real Estate	Food & Beverage	Health	Hospitality & Tourism	Manuf.	Nonrenewable Energy	Pharma & Health	Renewable Energy	Retail	Tech & Comms	Transport	Vice
Baseline	0.232	-0.289	0.047	0.549*	0.689*	0.111	-0.321	0.585*	0.050	0.424**	0.655***	-0.530**	0.313	0.184	0.677*	0.209*
	(0.218)	(0.376)	(0.338)	(0.289)	(0.367)	(0.255)	(0.304)	(0.342)	(0.345)	(0.175)	(0.207)	(0.237)	(0.317)	(0.135)	(0.358)	(0.115)
All Controls	0.308	-0.246	0.188	0.482**	0.835**	0.180	-0.303	0.673*	0.098	0.425**	0.762***	-0.444*	0.626**	0.169	0.780**	0.236
	(0.236)	(0.403)	(0.374)	(0.229)	(0.385)	(0.269)	(0.306)	(0.362)	(0.339)	(0.203)	(0.226)	(0.235)	(0.287)	(0.164)	(0.352)	(0.151)
Demographic Controls	0.475	-0.372	0.180	0.562	0.920**	0.484	-0.136	0.892**	0.334	0.849***	1.150***	-0.510	0.791***	0.536**	0.827**	0.628***
	(0.310)	(0.516)	(0.399)	(0.421)	(0.403)	(0.485)	(0.328)	(0.370)	(0.321)	(0.227)	(0.267)	(0.513)	(0.259)	(0.246)	(0.376)	(0.224)
No Controls	0.430	-0.257	0.144	0.566	0.854*	0.606	-0.188	0.836**	0.382	0.935***	1.109***	-0.613	0.693**	0.548*	0.763**	0.688***
	(0.376)	(0.522)	(0.364)	(0.507)	(0.483)	(0.539)	(0.360)	(0.358)	(0.327)	(0.326)	(0.289)	(0.479)	(0.296)	(0.300)	(0.376)	(0.238)
$100,000 Cap	0.221	-0.288	0.041	0.549*	0.644**	0.111	-0.309	0.585*	0.050	0.424**	0.655***	-0.530**	0.313	0.184	0.677*	0.209*
	(0.151)	(0.377)	(0.332)	(0.289)	(0.308)	(0.255)	(0.210)	(0.342)	(0.345)	(0.175)	(0.207)	(0.237)	(0.317)	(0.135)	(0.358)	(0.115)
$20,000 Cap	0.056	-0.222	0.035	0.531*	0.361	0.111	-0.012	0.585*	0.050	0.412**	0.657***	-0.530**	0.313	0.182	0.678*	0.193*
	(0.122)	(0.374)	(0.298)	(0.286)	(0.237)	(0.255)	(0.170)	(0.342)	(0.345)	(0.178)	(0.210)	(0.237)	(0.317)	(0.133)	(0.357)	(0.117)
12-Month Treatment	0.206	-0.041	-0.044	0.706***	0.542*	0.440*	-0.425	0.549	0.196	0.238	0.305	-0.440	0.484**	0.253*	0.400	0.422***
	(0.160)	(0.237)	(0.240)	(0.201)	(0.314)	(0.262)	(0.280)	(0.568)	(0.319)	(0.163)	(0.230)	(0.304)	(0.236)	(0.142)	(0.254)	(0.108)
Observations	7,728	6,688	5,734	5,464	7,194	4,672	7,436	1,786	4,491	6,288	5,167	1,284	3,891	6,408	5,864	5,678
Control Mean ($)	11,036	845	381	516	4,115	163	2,022	51	184	541	395	44	174	737	546	324

Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table D8: Effect of Fatal School Shootings in Competitive Districts on Contributions to Democrats Across Sectors, 2000–2024 (10% Competitiveness Threshold). Static PPML Model.

	All Corporate	Agriculture	Construction	Defense	Finance, Ins. & Real Estate	Food & Beverage	Health	Hospitality & Tourism	Manuf.	Nonrenewable Energy	Pharma & Health	Renewable Energy	Retail	Tech & Comms	Transport	Vice
Baseline	-0.006	0.207	-0.119	0.126	0.024	0.413	-0.394	0.026	-0.227	0.431*	0.217	-0.719**	-0.021	0.150	0.262	0.102
	(0.229)	(0.369)	(0.254)	(0.322)	(0.329)	(0.279)	(0.315)	(0.315)	(0.260)	(0.235)	(0.284)	(0.322)	(0.235)	(0.223)	(0.278)	(0.165)
All Controls	0.011	0.218	-0.098	0.092	-0.022	0.414	-0.309	0.035	-0.206	0.474**	0.145	-0.679**	0.004	0.151	0.309	0.068
	(0.235)	(0.400)	(0.254)	(0.303)	(0.350)	(0.299)	(0.316)	(0.310)	(0.260)	(0.234)	(0.296)	(0.282)	(0.250)	(0.226)	(0.281)	(0.173)
Demographic Controls	-0.128	-0.053	-0.264	-0.223	-0.110	0.249	-0.435	-0.013	-0.332	0.294	0.098	-0.602*	-0.091	0.055	0.017	0.055
	(0.266)	(0.280)	(0.231)	(0.449)	(0.393)	(0.262)	(0.331)	(0.287)	(0.269)	(0.228)	(0.341)	(0.333)	(0.229)	(0.256)	(0.283)	(0.180)
No Controls	-0.138	-0.067	-0.275	-0.177	-0.091	0.198	-0.449	0.009	-0.333	0.254	0.232	-0.707**	-0.090	0.075	-0.012	0.089
	(0.274)	(0.303)	(0.241)	(0.468)	(0.396)	(0.283)	(0.340)	(0.332)	(0.289)	(0.267)	(0.385)	(0.349)	(0.230)	(0.268)	(0.302)	(0.192)
$100,000 Cap	0.075	0.206	-0.121	0.126	0.066	0.413	-0.286	0.026	-0.227	0.431*	0.217	-0.719**	-0.021	0.150	0.262	0.102
	(0.186)	(0.369)	(0.254)	(0.322)	(0.248)	(0.279)	(0.261)	(0.315)	(0.260)	(0.235)	(0.284)	(0.322)	(0.235)	(0.223)	(0.278)	(0.165)
$20,000 Cap	0.004	0.256	-0.130	0.113	0.045	0.397	-0.093	0.026	-0.227	0.422*	0.212	-0.719**	-0.021	0.149	0.262	0.094
	(0.149)	(0.388)	(0.255)	(0.317)	(0.190)	(0.279)	(0.205)	(0.315)	(0.260)	(0.230)	(0.285)	(0.322)	(0.235)	(0.223)	(0.277)	(0.164)
12-Month Treatment	-0.120	-0.064	-0.209	0.215	0.006	0.396**	-0.496**	-0.017	-0.103	0.033	0.112	-0.416*	0.089	0.098	0.108	0.085
	(0.177)	(0.179)	(0.159)	(0.272)	(0.308)	(0.194)	(0.213)	(0.376)	(0.277)	(0.122)	(0.222)	(0.223)	(0.205)	(0.242)	(0.198)	(0.128)
Observations	15,948	14,323	13,325	11,864	15,168	11,518	15,435	5,821	11,633	13,434	11,838	4,050	9,680	14,052	13,510	13,348
Control Mean ($)	10,241	868	376	470	3,583	165	1,821	48	178	535	361	51	171	706	596	314

Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table D9: Effect of Fatal School Shootings in Competitive Districts on Contributions to Democrats, 2000–2024. Static Stacked PPML Model.

	All Corporate	Agriculture	Construction	Defense	Finance, Ins. & Real Estate	Food & Beverage	Health	Hospitality & Tourism	Manuf.	Nonrenewable Energy	Pharma & Health	Renewable Energy	Retail	Tech & Comms	Transport	Vice
Baseline	-0.174	0.353	0.020	0.902**	-0.415	0.595	-0.604**	1.030	-0.097	0.673**	0.548*	-0.136	0.699***	0.358	0.166	0.795***
	(0.211)	(0.442)	(0.344)	(0.353)	(0.466)	(0.748)	(0.263)	(0.801)	(0.576)	(0.301)	(0.306)	(0.385)	(0.267)	(0.251)	(0.411)	(0.273)
Demographic Controls	-0.212	0.371	0.142	0.923***	-0.435	0.637	-0.724**	0.888	-0.147	0.656**	0.223	0.023	0.688**	0.350	0.196	0.785***
	(0.235)	(0.440)	(0.263)	(0.313)	(0.505)	(0.781)	(0.285)	(0.800)	(0.587)	(0.310)	(0.389)	(0.381)	(0.276)	(0.247)	(0.385)	(0.252)
$100,000 Cap	0.034	0.353	0.020	0.902**	-0.242	0.595	-0.491*	1.030	-0.097	0.673**	0.548*	-0.136	0.699***	0.358	0.166	0.795***
	(0.186)	(0.442)	(0.344)	(0.353)	(0.455)	(0.748)	(0.252)	(0.801)	(0.576)	(0.301)	(0.306)	(0.385)	(0.267)	(0.251)	(0.411)	(0.273)
$20,000 Cap	0.148	0.434	0.019	0.894**	0.069	0.595	0.043	1.030	-0.097	0.681**	0.565*	-0.136	0.699***	0.363	0.166	0.796***
	(0.151)	(0.426)	(0.344)	(0.351)	(0.288)	(0.748)	(0.140)	(0.801)	(0.576)	(0.306)	(0.311)	(0.385)	(0.267)	(0.247)	(0.411)	(0.274)
Observations	10,872	7,610	7,004	5,056	8,320	4,545	9,810	1,888	4,681	7,104	5,356	1,384	3,845	7,008	6,303	6,208
Control Mean ($)	14,520	1,498	687	1,319	7,530	517	3,080	480	601	964	1,022	569	658	1,415	1,037	692

Note: static stacked pseudo-Poisson maximum likelihood difference-in-differences model; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; within each stack, districts and months with zero contributions in all observations are excluded prior to estimation. The treatment period runs from each shooting month to the end of the election cycle. Standard errors clustered by district in parentheses. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table D10: Effect of Fatal School Shootings on Contributions to Democrats by District Competitiveness, 2000–2024. Static PPML Model.

	Competitive (Within 5%)	Competitive (Within 10%)	Safe D (Over 5%)	Safe D (Over 10%)	Safe R (Over 5%)	Safe R (Over 10%)
Baseline	0.232	-0.006	0.006	0.027	0.881*	0.715
	(0.218)	(0.229)	(0.045)	(0.043)	(0.535)	(0.731)
All Controls	0.308	0.011	0.002	0.021	0.596	0.855
	(0.236)	(0.235)	(0.045)	(0.043)	(0.704)	(0.916)
Demographic Controls	0.475	-0.128	0.002	0.020	0.589	0.830
	(0.310)	(0.266)	(0.045)	(0.043)	(0.699)	(0.893)
No Controls	0.430	-0.138	0.006	0.027	0.880*	0.771
	(0.376)	(0.274)	(0.045)	(0.043)	(0.533)	(0.696)
$100,000 Cap	0.221	0.075	0.023	0.040	0.410	-0.014
	(0.151)	(0.186)	(0.041)	(0.040)	(0.394)	(0.501)
$20,000 Cap	0.056	0.004	0.013	0.025	0.339	-0.127
	(0.122)	(0.149)	(0.029)	(0.029)	(0.362)	(0.403)
12-Month Treatment	0.206	-0.120	0.002	0.022	0.877	1.169
	(0.160)	(0.177)	(0.043)	(0.043)	(0.681)	(0.715)
Observations	7,728	15,948	59,112	55,200	55,953	50,709
Control Mean ($)	11,036	10,241	15,874	15,669	555	476

Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

3. Log-Linear Specification

PPML requires dropping all units or time periods in which the outcome is zero for all observations. This affects under 3% of observations in our main analysis of total corporate contributions to Republicans, though the proportion is higher for the sector-disaggregated contributions.

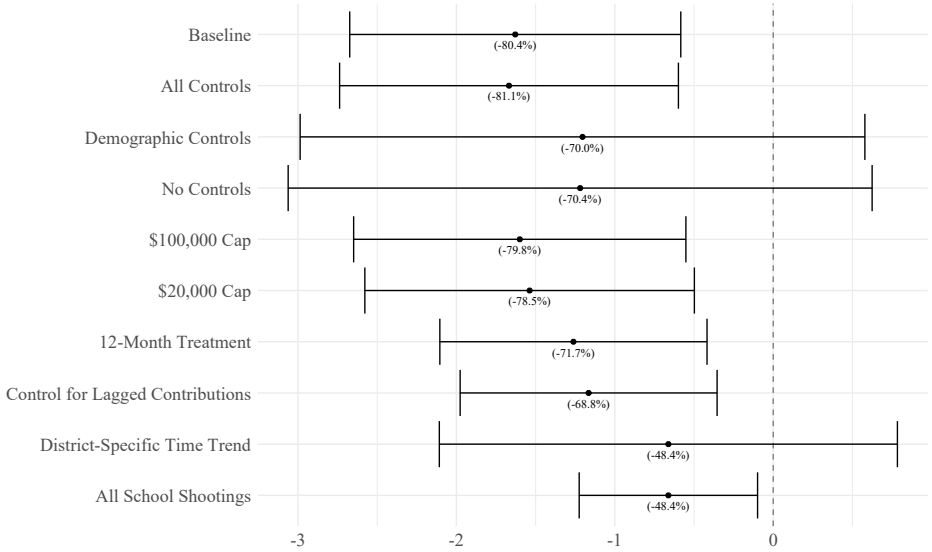
The zero-dropping in PPML is advantageous in our setting, as it removes uninformative observations. For example, if Republicans in a given district received zero contributions before a fatal school shooting and zero after, that district isn't evidence against our corporate divestment hypothesis; it simply provides no information about corporate divestment behavior. PPML ensures the district does not affect our baseline coefficient estimates.

For transparency, we estimate our main effects via log-linear OLS regression, as described in Equation D1.

$$E(\ln(1 + \text{Contrib}_{dm})|\cdot) = \gamma_d + \lambda_m + \delta FSS_{dm} + x'_{dm}\beta \tag{D1}$$

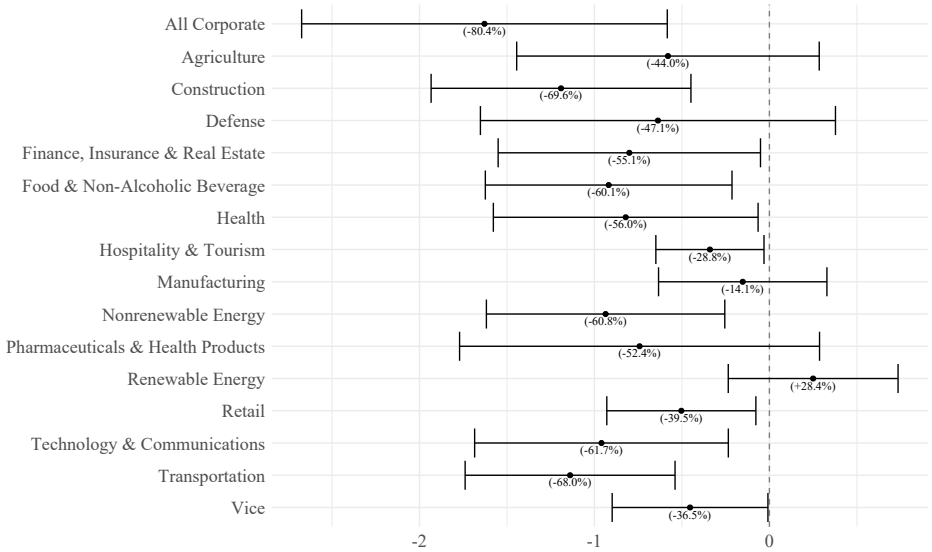
As log-linear regression does not require zero-dropping, the consistency of the log-linear results provides reassurance. The one exception is corporate contributions to Republicans in safe Democratic districts, where the log-linear and PPML estimates diverge. This divergence is mechanical, as Republican challengers in safe Democratic districts attract little corporate money, producing a high proportion of all-zero districts. PPML drops these uninformative observations, while log-linear OLS retains them. The PPML result is therefore more credible in this specific case, and the divergence reflects the estimators' different treatments of sparse data rather than genuine fragility in the underlying finding.

Figure D11: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Specifications, 2000–2024. Static Log-Linear Model.



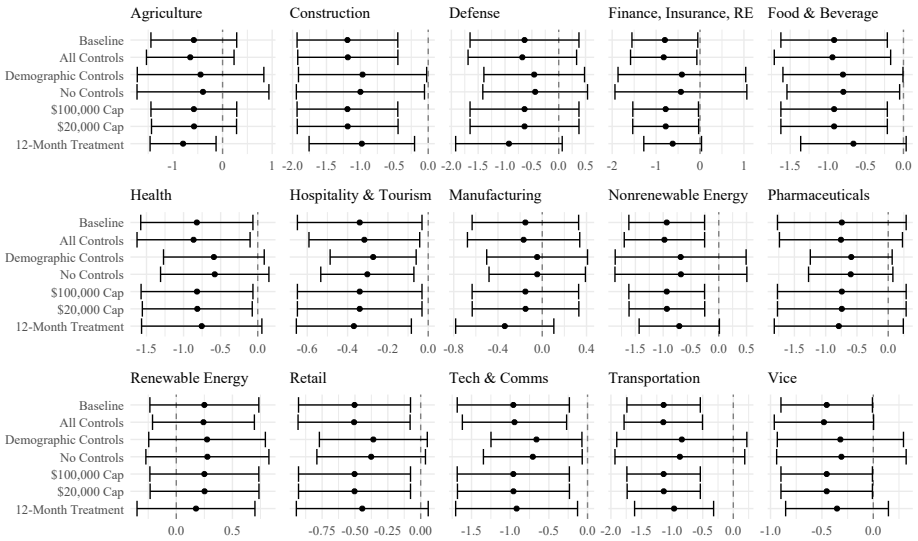
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; dollar amounts are nominal; exponentiating them yields multiplicative effects on contributions. When controlling for lagged contributions, the variance-covariance matrix could not be verified as positive semi-definite; interpret with caution. Standard errors are clustered by district.

Figure D12: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Sectors, 2000–2024. Static Log-Linear Model.



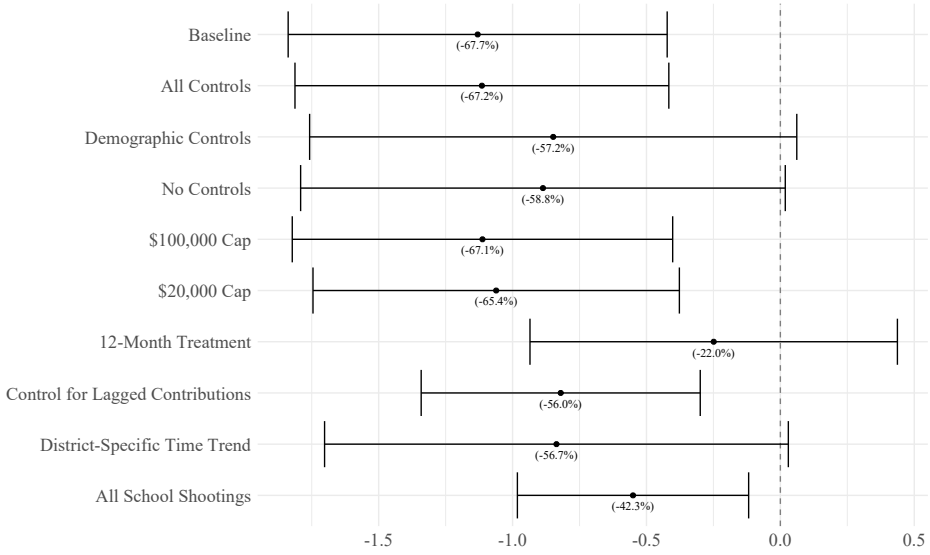
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D13: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Sectors and Specifications, 2000–2024. Static Log-Linear Model.



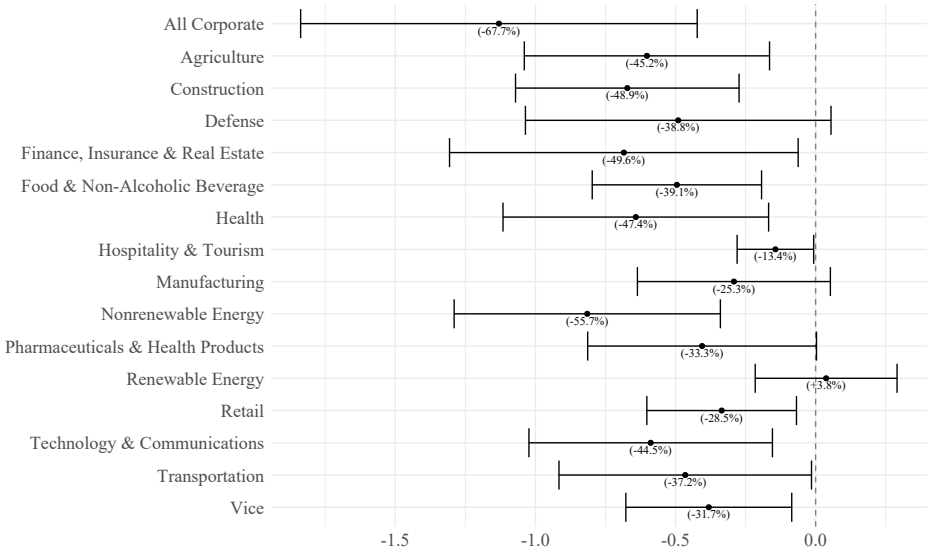
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D14: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Specifications (10% Competitiveness Threshold), 2000–2024. Static Log-Linear Model.



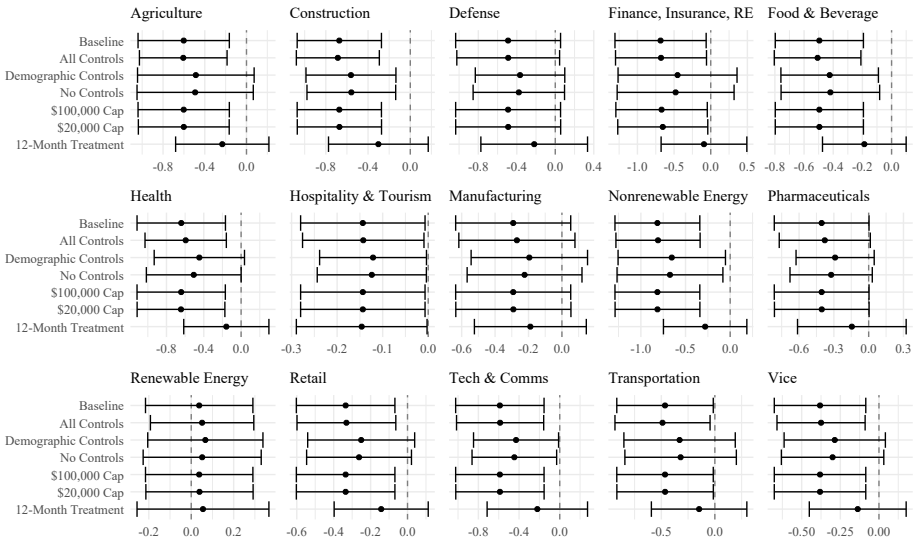
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. When controlling for lagged contributions, the variance-covariance matrix could not be verified as positive semi-definite; interpret with caution. Standard errors are clustered by district.

Figure D15: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Sectors (10% Competitiveness Threshold), 2000–2024. Static Log-Linear Model.



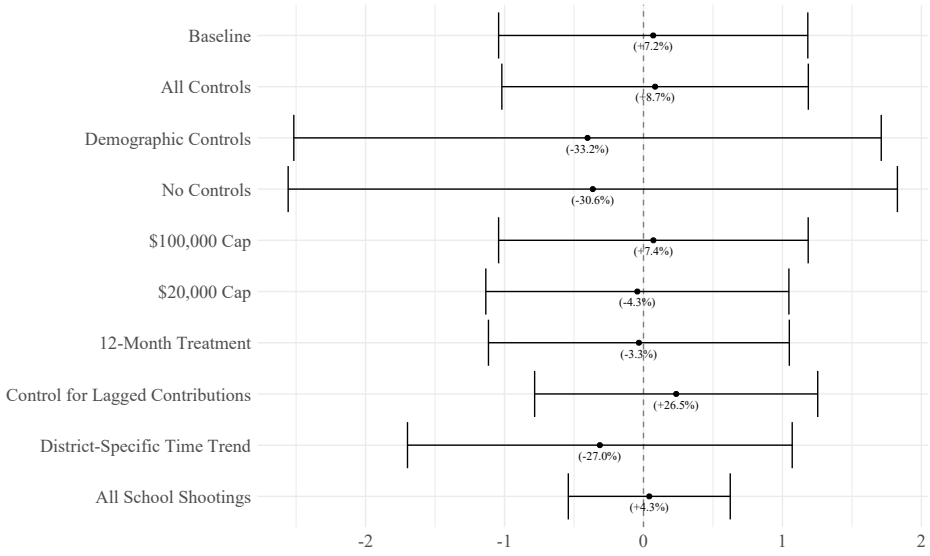
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D16: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Sectors and Specifications (10% Competitiveness Threshold), 2000–2024. Static Log-Linear Model.



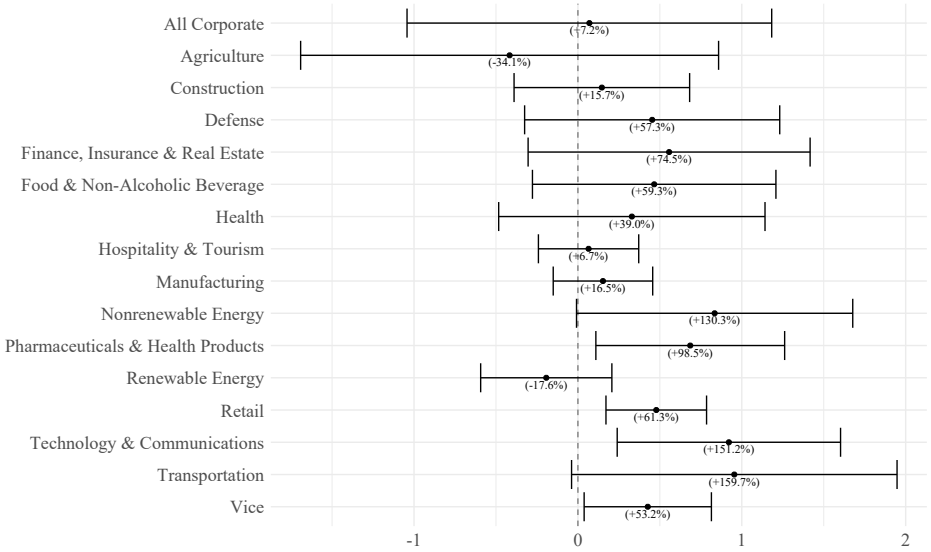
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D17: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts Across Specifications, 2000–2024. Static Log-Linear Model.



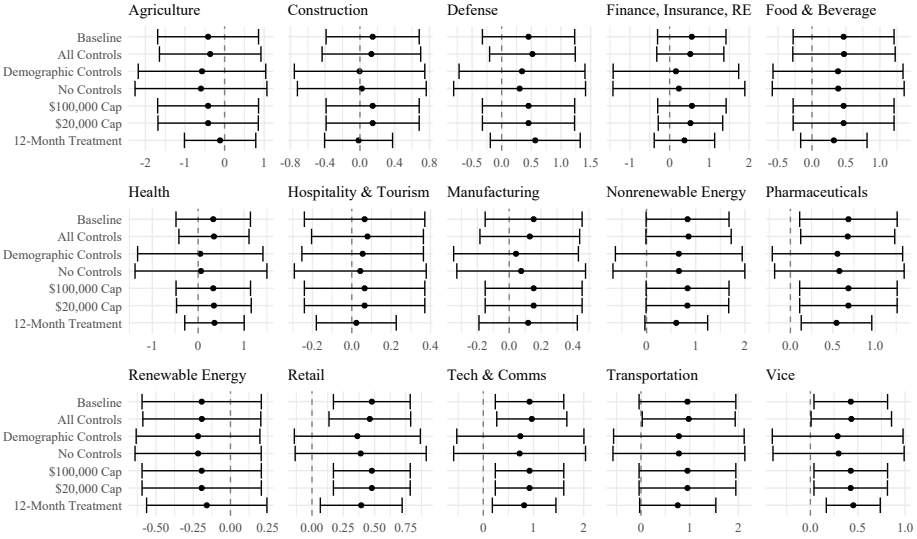
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. When controlling for lagged contributions, the variance-covariance matrix could not be verified as positive semi-definite; interpret with caution. Standard errors are clustered by district.

Figure D18: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts Across Sectors, 2000–2024. Static Log-Linear Model.



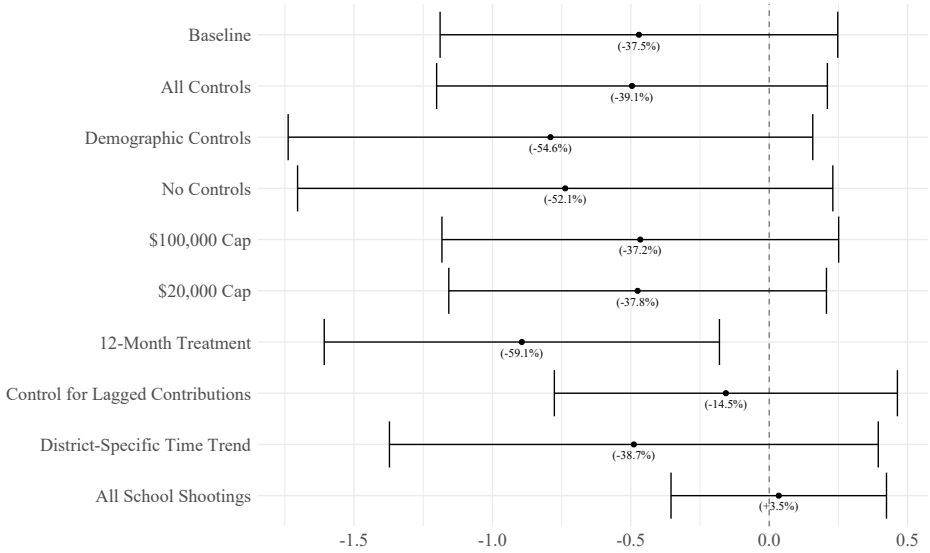
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D19: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts Across Sectors and Specifications, 2000–2024. Static Log-Linear Model.



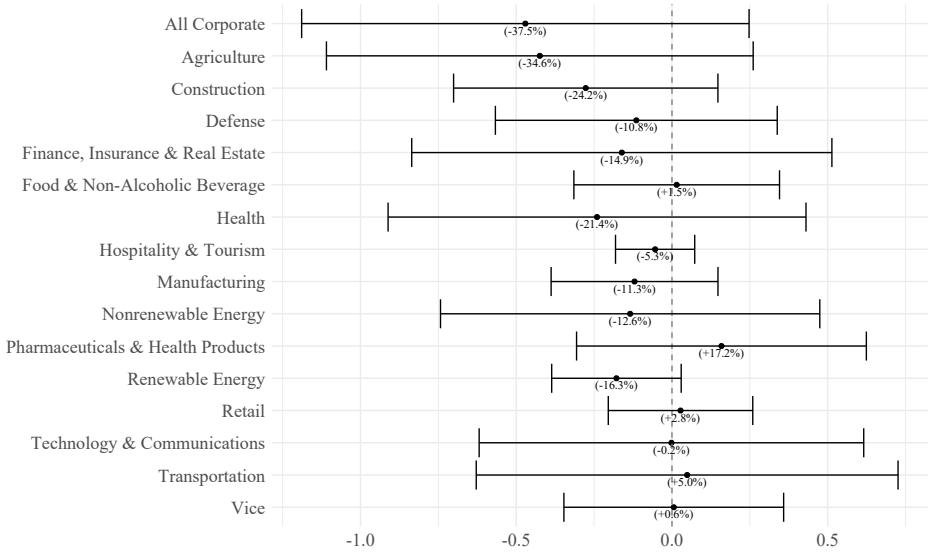
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D20: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts Across Specifications (10% Competitiveness Threshold), 2000–2024. Static Log-Linear Model.



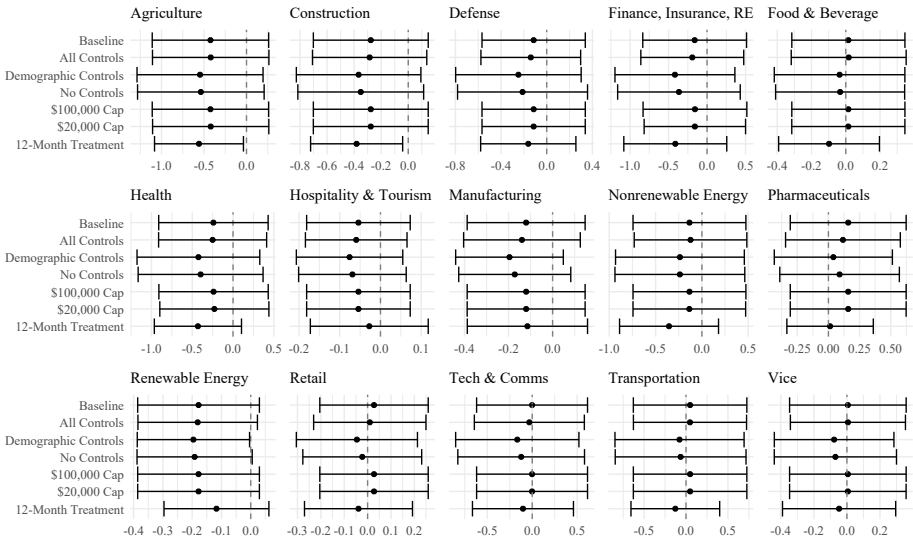
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. When controlling for lagged contributions, the variance-covariance matrix could not be verified as positive semi-definite; interpret with caution. Standard errors are clustered by district.

Figure D21: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts Across Sectors (10% Competitiveness Threshold), 2000–2024. Static Log-Linear Model.



Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D22: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts Across Sectors and Specifications (10% Competitiveness Threshold), 2000–2024. Static Log-Linear Model.



Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Table D11: Effect of Fatal School Shootings in Competitive Districts on Contributions to Republicans Across Sectors, 2000–2024. Static Log-Linear Model.

	All Corporate	Agriculture	Construction	Defense	Finance, Ins. & Real Estate	Food & Beverage	Health	Hospitality & Tourism	Manuf.	Nonrenewable Energy	Pharma & Health	Renewable Energy	Retail	Tech & Comms	Transport	Vice
Baseline	-1.629***	-0.580	-1.191***	-0.637	-0.801**	-0.919**	-0.821**	-0.340**	-0.152	-0.936***	-0.742	0.250	-0.503**	-0.960***	-1.139***	-0.454**
	(0.533)	(0.441)	(0.379)	(0.518)	(0.383)	(0.360)	(0.386)	(0.158)	(0.246)	(0.348)	(0.525)	(0.248)	(0.217)	(0.370)	(0.306)	(0.227)
All Controls	-1.668***	-0.652	-1.185***	-0.678	-0.827**	-0.940**	-0.865**	-0.317**	-0.169	-0.978***	-0.756	0.242	-0.507**	-0.944***	-1.144***	-0.481*
	(0.546)	(0.450)	(0.377)	(0.516)	(0.385)	(0.393)	(0.389)	(0.140)	(0.259)	(0.369)	(0.502)	(0.232)	(0.218)	(0.344)	(0.327)	(0.246)
Demographic Controls	-1.204	-0.444	-0.968**	-0.456	-0.413	-0.802**	-0.591*	-0.273**	-0.046	-0.685	-0.591*	0.274	-0.360*	-0.660**	-0.842	-0.320
	(0.909)	(0.651)	(0.482)	(0.478)	(0.742)	(0.406)	(0.347)	(0.109)	(0.232)	(0.601)	(0.334)	(0.265)	(0.209)	(0.300)	(0.542)	(0.313)
No Controls	-1.219	-0.395	-1.000**	-0.438	-0.435	-0.797**	-0.580	-0.302**	-0.045	-0.681	-0.600*	0.277	-0.377*	-0.708**	-0.874	-0.310
	(0.940)	(0.678)	(0.482)	(0.498)	(0.766)	(0.381)	(0.373)	(0.118)	(0.222)	(0.605)	(0.344)	(0.280)	(0.211)	(0.326)	(0.541)	(0.321)
$100,000 Cap	-1.600***	-0.579	-1.191***	-0.637	-0.783**	-0.919**	-0.819**	-0.340**	-0.152	-0.936***	-0.742	0.250	-0.503**	-0.960***	-1.139***	-0.454**
	(0.535)	(0.441)	(0.379)	(0.518)	(0.381)	(0.360)	(0.385)	(0.158)	(0.246)	(0.348)	(0.525)	(0.248)	(0.217)	(0.370)	(0.306)	(0.227)
$20,000 Cap	-1.538***	-0.576	-1.188***	-0.637	-0.782**	-0.919**	-0.815**	-0.340**	-0.151	-0.933***	-0.742	0.252	-0.503**	-0.958***	-1.137***	-0.454**
	(0.531)	(0.437)	(0.379)	(0.518)	(0.383)	(0.360)	(0.378)	(0.158)	(0.246)	(0.347)	(0.525)	(0.247)	(0.217)	(0.369)	(0.305)	(0.227)
12-Month Treatment	-1.261***	-0.796**	-0.979**	-0.927*	-0.623*	-0.663*	-0.755*	-0.369**	-0.339	-0.711*	-0.790	0.175	-0.444*	-0.917**	-0.968***	-0.353
	(0.430)	(0.339)	(0.397)	(0.506)	(0.335)	(0.356)	(0.414)	(0.146)	(0.226)	(0.368)	(0.526)	(0.268)	(0.256)	(0.402)	(0.329)	(0.255)
Observations	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220
Control Mean ($)	18,784	1,234	1,323	652	6,626	621	2,123	82	365	1,738	542	74	401	1,050	1,442	509

Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table D12: Effect of Fatal School Shootings in Competitive Districts on Contributions to Republicans Across Sectors, 2000–2024 (10% Competitiveness Threshold). Static Log-Linear Model.

	All Corporate	Agriculture	Construction	Defense	Finance, Ins. & Real Estate	Food & Beverage	Health	Hospitality & Tourism	Manuf.	Nonrenewable Energy	Pharma & Health	Renewable Energy	Retail	Tech & Comms	Transport	Vice
Baseline	-1.130***	-0.602***	-0.672***	-0.490*	-0.684**	-0.495***	-0.642***	-0.144**	-0.292*	-0.815***	-0.405*	0.038	-0.335**	-0.589***	-0.465**	-0.381**
	(0.361)	(0.223)	(0.204)	(0.278)	(0.317)	(0.154)	(0.242)	(0.070)	(0.176)	(0.242)	(0.208)	(0.129)	(0.136)	(0.222)	(0.230)	(0.151)
All Controls	-1.114***	-0.606***	-0.686***	-0.489*	-0.678**	-0.507***	-0.594***	-0.143**	-0.269	-0.808***	-0.378*	0.051	-0.331**	-0.586***	-0.489**	-0.375**
	(0.356)	(0.214)	(0.200)	(0.273)	(0.317)	(0.151)	(0.222)	(0.068)	(0.177)	(0.240)	(0.200)	(0.124)	(0.137)	(0.219)	(0.227)	(0.145)
Demographic Controls	-0.848*	-0.486*	-0.562***	-0.366	-0.453	-0.424**	-0.448*	-0.121**	-0.195	-0.654**	-0.289*	0.066	-0.251*	-0.429**	-0.329	-0.286*
	(0.464)	(0.285)	(0.217)	(0.237)	(0.414)	(0.171)	(0.247)	(0.060)	(0.178)	(0.307)	(0.172)	(0.139)	(0.148)	(0.213)	(0.265)	(0.167)
No Controls	-0.887*	-0.492*	-0.558***	-0.379	-0.479	-0.420**	-0.508*	-0.124**	-0.224	-0.674**	-0.323*	0.052	-0.263*	-0.446**	-0.320	-0.300*
	(0.462)	(0.284)	(0.214)	(0.242)	(0.407)	(0.172)	(0.259)	(0.061)	(0.175)	(0.302)	(0.181)	(0.142)	(0.145)	(0.212)	(0.266)	(0.169)
$100,000 Cap	-1.112***	-0.602***	-0.672***	-0.490*	-0.671**	-0.495***	-0.642***	-0.144**	-0.292*	-0.815***	-0.405*	0.038	-0.335**	-0.589***	-0.465**	-0.381**
	(0.362)	(0.223)	(0.204)	(0.278)	(0.318)	(0.154)	(0.242)	(0.070)	(0.176)	(0.242)	(0.208)	(0.129)	(0.136)	(0.222)	(0.230)	(0.151)
$20,000 Cap	-1.061***	-0.601***	-0.671***	-0.490*	-0.654**	-0.495***	-0.644***	-0.144**	-0.291*	-0.814***	-0.404*	0.039	-0.335**	-0.588***	-0.465**	-0.381**
	(0.349)	(0.222)	(0.203)	(0.278)	(0.313)	(0.154)	(0.240)	(0.070)	(0.176)	(0.242)	(0.208)	(0.129)	(0.136)	(0.221)	(0.230)	(0.151)
12-Month Treatment	-0.249	-0.232	-0.302	-0.219	-0.092	-0.187	-0.158	-0.146**	-0.189	-0.280	-0.145	0.055	-0.143	-0.220	-0.147	-0.137
	(0.350)	(0.228)	(0.241)	(0.283)	(0.298)	(0.146)	(0.233)	(0.073)	(0.171)	(0.238)	(0.239)	(0.159)	(0.130)	(0.252)	(0.227)	(0.160)
Observations	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668
Control Mean ($)	16,900	1,066	1,144	630	5,961	547	1,913	75	348	1,539	503	60	368	989	1,291	465

Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table D13: Effect of Fatal School Shootings in Competitive Districts on Contributions to Democrats Across Sectors, 2000–2024. Static Log-Linear Model.

	All Corporate	Agriculture	Construction	Defense	Finance, Ins. & Real Estate	Food & Beverage	Health	Hospitality & Tourism	Manuf.	Nonrenewable Energy	Pharma & Health	Renewable Energy	Retail	Tech & Comms	Transport	Vice
Baseline	0.070	-0.417	0.146	0.453	0.556	0.465	0.329	0.065	0.153	0.834*	0.686**	-0.193	0.478***	0.921***	0.954*	0.426**
	(0.568)	(0.651)	(0.273)	(0.397)	(0.439)	(0.379)	(0.415)	(0.156)	(0.155)	(0.430)	(0.294)	(0.204)	(0.157)	(0.348)	(0.507)	(0.198)
All Controls	0.083	-0.364	0.132	0.518	0.520	0.471	0.345	0.080	0.129	0.854*	0.677**	-0.192	0.462***	0.966***	0.980**	0.432**
	(0.563)	(0.655)	(0.289)	(0.369)	(0.430)	(0.384)	(0.391)	(0.145)	(0.159)	(0.442)	(0.283)	(0.202)	(0.167)	(0.356)	(0.487)	(0.217)
Demographic Controls	-0.403	-0.571	-0.004	0.343	0.158	0.383	0.047	0.055	0.043	0.656	0.556	-0.218	0.363	0.738	0.778	0.288
	(1.078)	(0.822)	(0.383)	(0.542)	(0.805)	(0.488)	(0.698)	(0.158)	(0.199)	(0.658)	(0.393)	(0.212)	(0.257)	(0.646)	(0.684)	(0.352)
No Controls	-0.365	-0.597	0.021	0.302	0.233	0.386	0.062	0.043	0.075	0.658	0.579	-0.217	0.389	0.723	0.779	0.298
	(1.119)	(0.851)	(0.378)	(0.568)	(0.846)	(0.495)	(0.735)	(0.171)	(0.206)	(0.684)	(0.390)	(0.216)	(0.267)	(0.670)	(0.691)	(0.353)
$100,000 Cap	0.071	-0.417	0.146	0.453	0.560	0.465	0.331	0.065	0.153	0.834*	0.686**	-0.193	0.478***	0.921***	0.954*	0.426**
	(0.568)	(0.651)	(0.273)	(0.397)	(0.439)	(0.379)	(0.415)	(0.156)	(0.155)	(0.430)	(0.294)	(0.204)	(0.157)	(0.348)	(0.507)	(0.198)
$20,000 Cap	-0.044	-0.416	0.146	0.452	0.524	0.465	0.344	0.065	0.153	0.830*	0.685**	-0.193	0.478***	0.921***	0.954*	0.426**
	(0.556)	(0.647)	(0.273)	(0.397)	(0.414)	(0.379)	(0.416)	(0.156)	(0.155)	(0.429)	(0.294)	(0.204)	(0.157)	(0.348)	(0.507)	(0.198)
12-Month Treatment	-0.033	-0.113	-0.016	0.567	0.372	0.322	0.356	0.023	0.118	0.604*	0.545**	-0.159	0.393**	0.814**	0.755*	0.453***
	(0.552)	(0.460)	(0.200)	(0.387)	(0.388)	(0.249)	(0.331)	(0.104)	(0.157)	(0.326)	(0.213)	(0.206)	(0.167)	(0.323)	(0.399)	(0.145)
Observations	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220	8,220
Control Mean ($)	11,036	845	381	516	4,115	163	2,022	51	184	541	395	44	174	737	546	324

Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table D14: Effect of Fatal School Shootings in Competitive Districts on Contributions to Democrats Across Sectors, 2000–2024 (10% Competitiveness Threshold). Static Log-Linear Model.

	All Corporate	Agriculture	Construction	Defense	Finance, Ins. & Real Estate	Food & Beverage	Health	Hospitality & Tourism	Manuf.	Nonrenewable Energy	Pharma & Health	Renewable Energy	Retail	Tech & Comms	Transport	Vice
Baseline	-0.471	-0.424	-0.277	-0.115	-0.161	0.015	-0.241	-0.054	-0.120	-0.134	0.159	-0.178*	0.027	-0.002	0.049	0.006
	(0.366)	(0.350)	(0.216)	(0.231)	(0.344)	(0.168)	(0.342)	(0.065)	(0.137)	(0.311)	(0.237)	(0.106)	(0.118)	(0.315)	(0.345)	(0.180)
All Controls	-0.496	-0.421	-0.285	-0.140	-0.192	0.017	-0.250	-0.060	-0.139	-0.123	0.117	-0.181*	0.009	-0.032	0.047	0.006
	(0.360)	(0.350)	(0.215)	(0.223)	(0.341)	(0.171)	(0.338)	(0.064)	(0.135)	(0.310)	(0.235)	(0.104)	(0.123)	(0.312)	(0.344)	(0.178)
Demographic Controls	-0.790	-0.547	-0.367	-0.248	-0.418	-0.036	-0.425	-0.076	-0.196	-0.237	0.039	-0.196**	-0.046	-0.166	-0.077	-0.077
	(0.483)	(0.378)	(0.235)	(0.281)	(0.398)	(0.194)	(0.384)	(0.067)	(0.125)	(0.354)	(0.242)	(0.098)	(0.132)	(0.350)	(0.393)	(0.185)
No Controls	-0.737	-0.537	-0.351	-0.212	-0.365	-0.033	-0.398	-0.069	-0.172	-0.238	0.090	-0.192*	-0.023	-0.123	-0.064	-0.070
	(0.493)	(0.380)	(0.237)	(0.290)	(0.406)	(0.192)	(0.391)	(0.067)	(0.130)	(0.357)	(0.245)	(0.100)	(0.130)	(0.360)	(0.398)	(0.189)
$100,000 Cap	-0.466	-0.424	-0.277	-0.115	-0.157	0.015	-0.239	-0.054	-0.120	-0.134	0.159	-0.178*	0.027	-0.002	0.049	0.006
	(0.366)	(0.350)	(0.216)	(0.231)	(0.344)	(0.168)	(0.342)	(0.065)	(0.137)	(0.311)	(0.237)	(0.106)	(0.118)	(0.315)	(0.345)	(0.180)
$20,000 Cap	-0.475	-0.421	-0.277	-0.115	-0.159	0.015	-0.229	-0.054	-0.120	-0.136	0.159	-0.178*	0.027	-0.002	0.049	0.006
	(0.348)	(0.349)	(0.216)	(0.231)	(0.336)	(0.168)	(0.341)	(0.065)	(0.137)	(0.310)	(0.237)	(0.106)	(0.118)	(0.315)	(0.345)	(0.180)
12-Month Treatment	-0.894**	-0.559**	-0.381**	-0.162	-0.413	-0.098	-0.431	-0.027	-0.114	-0.355	0.013	-0.117	-0.039	-0.103	-0.128	-0.047
	(0.364)	(0.267)	(0.173)	(0.213)	(0.341)	(0.150)	(0.273)	(0.074)	(0.139)	(0.272)	(0.177)	(0.091)	(0.118)	(0.287)	(0.270)	(0.175)
Observations	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668	16,668
Control Mean ($)	10,241	868	376	470	3,583	165	1,821	48	178	535	361	51	171	706	596	314

Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table D15: Effect of Fatal School Shootings on Contributions to Republicans by District Competitiveness, 2000–2024. Static Log-Linear Model.

	Competitive (Within 5%)	Competitive (Within 10%)	Safe D (Over 5%)	Safe D (Over 10%)	Safe R (Over 5%)	Safe R (Over 10%)
Baseline	-1.629***	-1.130***	0.012	-0.049	-0.015	0.170
	(0.533)	(0.361)	(0.051)	(0.047)	(0.209)	(0.202)
All Controls	-1.668***	-1.114***	0.013	-0.045	-0.017	0.167
	(0.546)	(0.356)	(0.053)	(0.048)	(0.204)	(0.203)
Demographic Controls	-1.204	-0.848*	0.013	-0.045	-0.026	0.150
	(0.909)	(0.464)	(0.054)	(0.048)	(0.205)	(0.204)
No Controls	-1.219	-0.887*	0.012	-0.049	-0.019	0.159
	(0.940)	(0.462)	(0.051)	(0.047)	(0.209)	(0.204)
$100,000 Cap	-1.600***	-1.112***	0.012	-0.049	-0.015	0.168
	(0.535)	(0.362)	(0.051)	(0.047)	(0.209)	(0.202)
$20,000 Cap	-1.538***	-1.061***	0.012	-0.046	-0.025	0.154
	(0.531)	(0.349)	(0.050)	(0.046)	(0.196)	(0.189)
12-Month Treatment	-1.261***	-0.249	0.042	-0.036	0.090	0.206
	(0.430)	(0.350)	(0.063)	(0.058)	(0.190)	(0.191)
Observations	8,220	16,668	59,160	55,224	62,328	57,816
Control Mean ($)	18,784	16,900	830	651	22,984	22,821

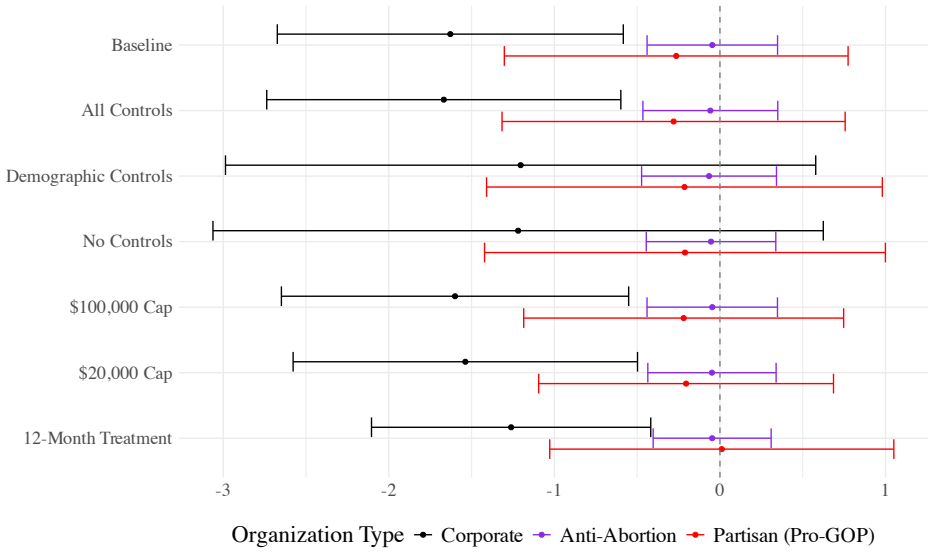
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table D16: Effect of Fatal School Shootings on Contributions to Democrats by District Competitiveness, 2000–2024. Static Log-Linear Model.

	Competitive (Within 5%)	Competitive (Within 10%)	Safe D (Over 5%)	Safe D (Over 10%)	Safe R (Over 5%)	Safe R (Over 10%)
Baseline	0.070	-0.471	-0.011	0.045	0.102	0.019
	(0.568)	(0.366)	(0.147)	(0.152)	(0.108)	(0.092)
All Controls	0.083	-0.496	-0.027	0.022	0.081	0.009
	(0.563)	(0.360)	(0.147)	(0.153)	(0.101)	(0.092)
Demographic Controls	-0.403	-0.790	-0.027	0.022	0.079	0.014
	(1.078)	(0.483)	(0.148)	(0.153)	(0.101)	(0.091)
No Controls	-0.365	-0.737	-0.011	0.045	0.095	0.019
	(1.119)	(0.493)	(0.147)	(0.152)	(0.109)	(0.093)
$100,000 Cap	0.071	-0.466	-0.010	0.045	0.100	0.017
	(0.568)	(0.366)	(0.147)	(0.152)	(0.108)	(0.092)
$20,000 Cap	-0.044	-0.475	-0.016	0.035	0.098	0.016
	(0.556)	(0.348)	(0.139)	(0.144)	(0.106)	(0.090)
12-Month Treatment	-0.033	-0.894**	-0.006	0.068	0.076	0.100
	(0.552)	(0.364)	(0.151)	(0.153)	(0.120)	(0.131)
Observations	8,220	16,668	59,160	55,224	62,328	57,816
Control Mean ($)	11,036	10,241	15,874	15,669	555	476

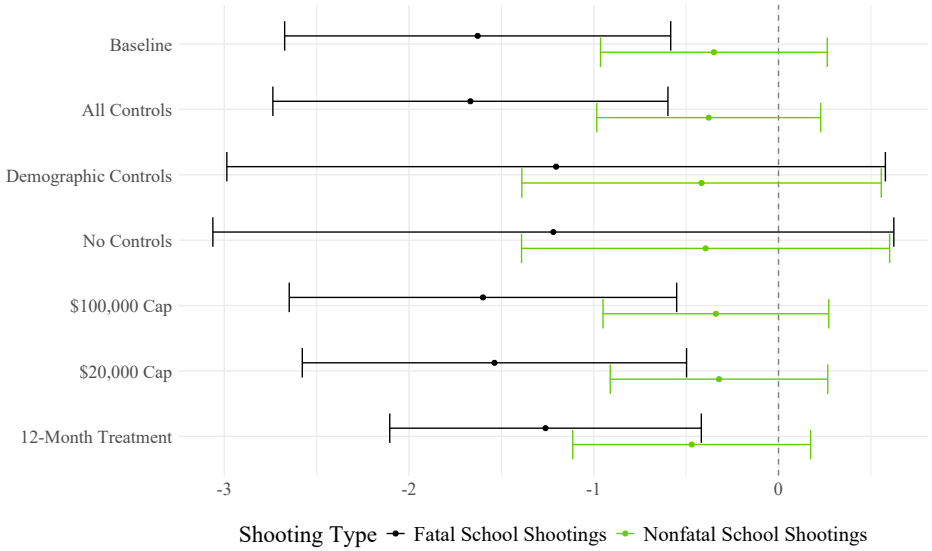
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Figure D23: Effect of Fatal School Shootings on Contributions to Republicans in Competitive Districts is Unique to Corporations, 2000–2024. Static Log-Linear Model.



Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

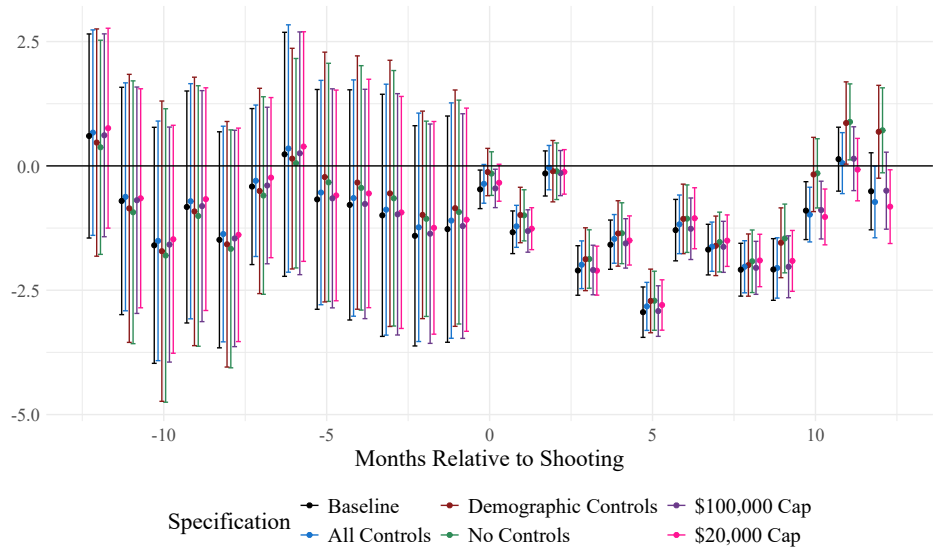
Figure D24: Only Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Specifications, 2000–2024. Static Log-Linear Model.



Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

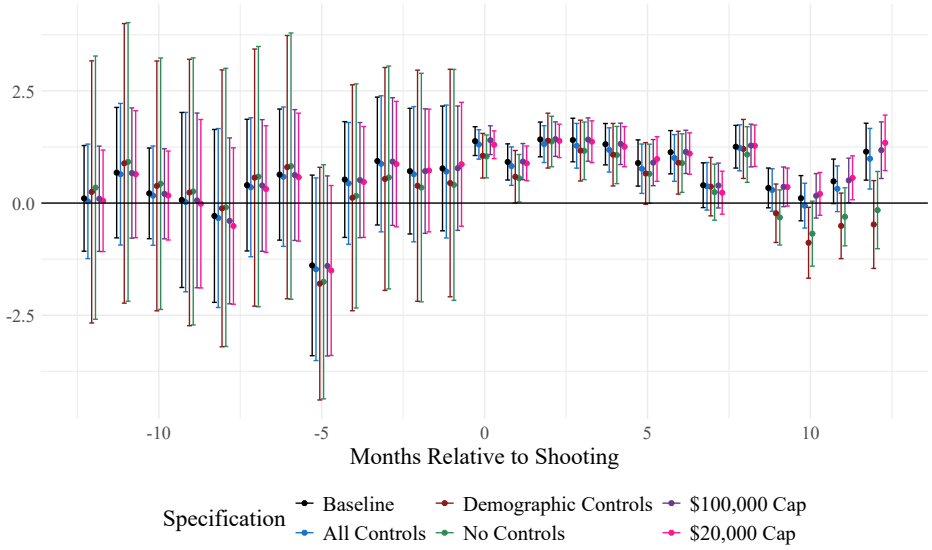
4. Staggered Treatment Estimators

Figure D25: Corporate Contributions to Republicans in Competitive Districts Return to Baseline Nine to Ten Months After Fatal School Shootings, 2000–2024. Imputation Model.



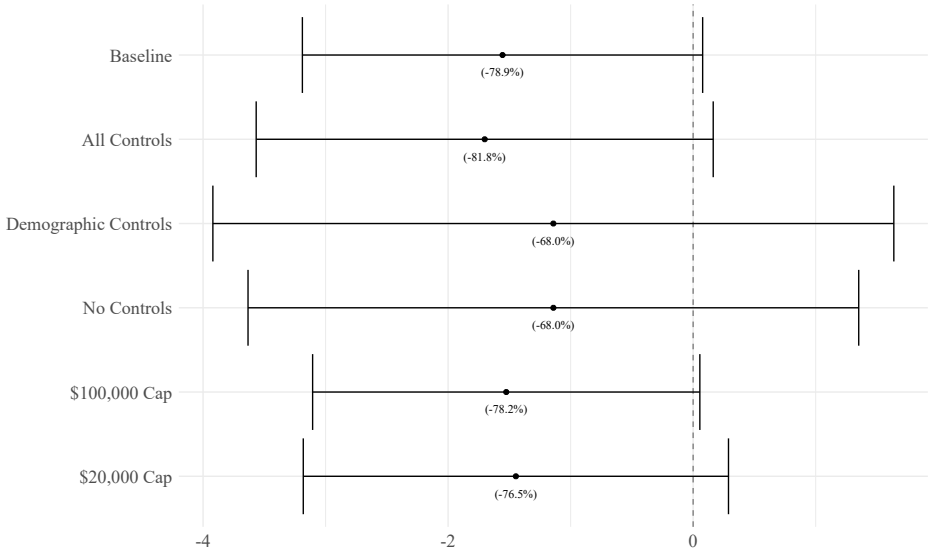
Note: imputation model based on Borusyak et al. (2024); coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district. Pre-trends and post-trends are computed using different processes in this model, leading to different standard error magnitudes.

Figure D26: Fatal School Shootings Minimally Impact Corporate Contributions to Democrats in Competitive Districts, 2000–2024. Imputation Model.



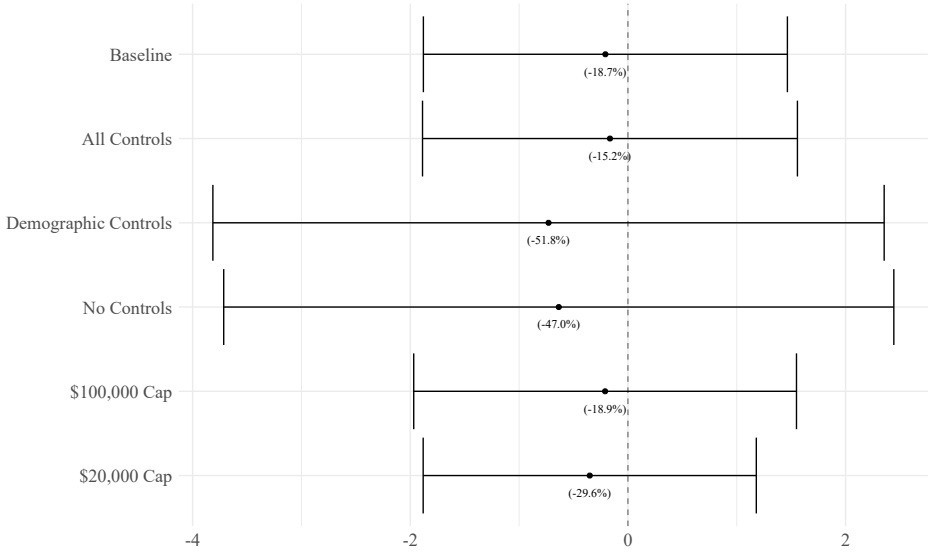
Note: imputation model based on Borusyak et al. (2024); coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district. Pre-trends and post-trends are computed using different processes in this model, leading to different standard error magnitudes.

Figure D27: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Specifications, 2000–2024. Interactive Fixed Effects Model.



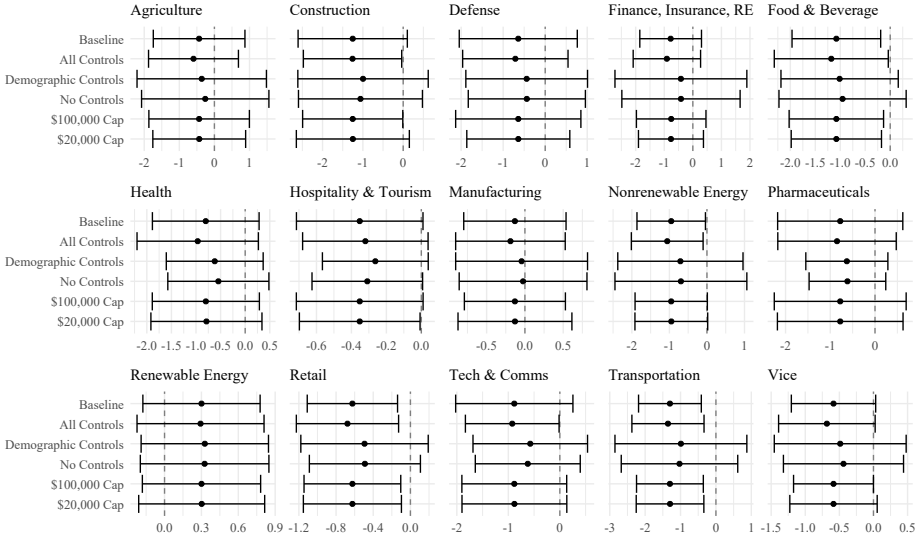
Note: interactive fixed effects approach of Liu et al. (2024); coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; units with less than 5 untreated observations are dropped from the sample. Standard errors are clustered by district.

Figure D28: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts Across Specifications, 2000–2024. Interactive Fixed Effects Model.



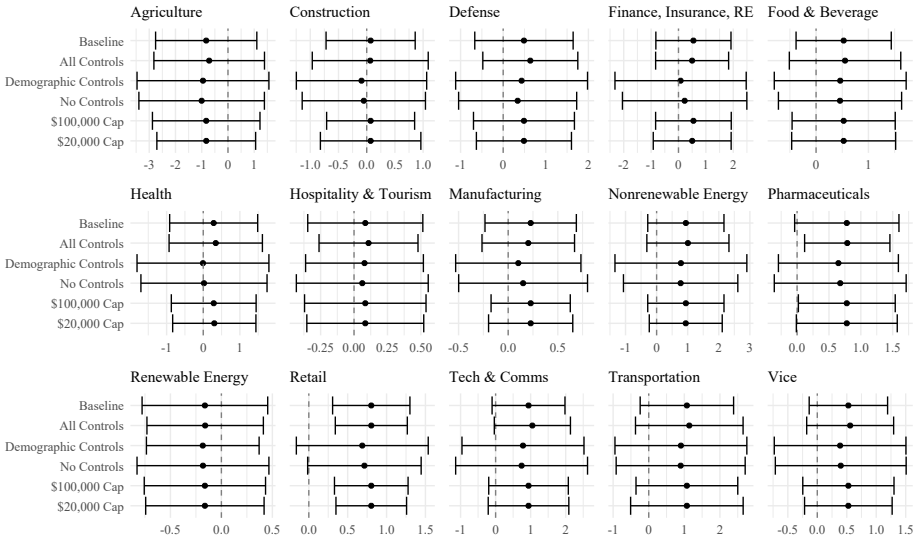
Note: interactive fixed effects approach of Liu et al. (2024); coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; units with less than 5 untreated observations are dropped from the sample. Standard errors are clustered by district.

Figure D29: Fatal School Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Sectors and Specifications, 2000–2024. Interactive Fixed Effects Model.



Note: interactive fixed effects approach of Liu et al. (2024); coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; units with less than 5 untreated observations are dropped from the sample. Standard errors are clustered by district.

Figure D30: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts Across Sectors and Specifications, 2000–2024. Interactive Fixed Effects Model.



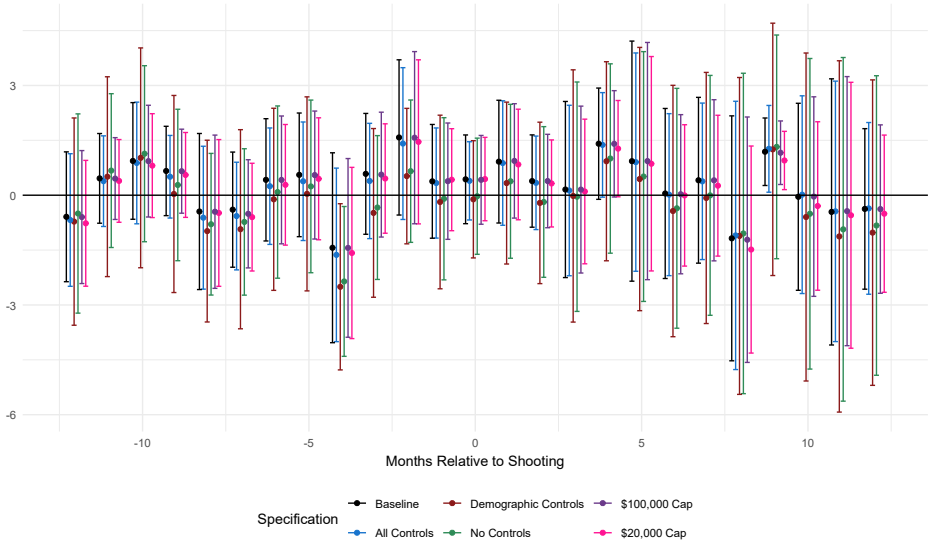
Note: interactive fixed effects approach of Liu et al. (2024); coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; units with less than 5 untreated observations are dropped from the sample. Standard errors are clustered by district.

Figure D31: Corporate Contributions to Republicans in Competitive Districts Return to Baseline Nine to Ten Months After Fatal School Shootings, 2000–2024. Interactive Fixed Effects Model.



Note: interactive fixed effects approach of Liu et al. (2024); coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; units with less than 5 untreated observations are dropped from the sample. Standard errors are clustered by district.

Figure D32: Fatal School Shootings Don't Impact Corporate Contributions to Democrats in Competitive Districts, 2000–2024. Interactive Fixed Effects Model.



Note: interactive fixed effects approach of Liu et al. (2024); coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; units with less than 5 untreated observations are dropped from the sample. Standard errors are clustered by district.

Table D17: Effect of Fatal School Shootings in Competitive Districts on Contributions to Republicans, 2000–2024. Interactive Fixed Effects Model.

	All Corporate	Agriculture	Construction	Defense	Finance, Ins. & Real Estate	Food & Beverage	Health	Hospitality & Tourism	Manuf.	Nonrenewable Energy	Pharma & Health	Renewable Energy	Retail	Tech & Comms	Transport	Vice
Baseline	-1.556*	-0.436	-1.252*	-0.641	-0.776	-1.078**	-0.802	-0.353*	-0.131	-0.952**	-0.778	0.301	-0.624**	-0.884	-1.300***	-0.586*
	(0.833)	(0.666)	(0.691)	(0.716)	(0.551)	(0.453)	(0.553)	(0.185)	(0.341)	(0.465)	(0.714)	(0.243)	(0.248)	(0.581)	(0.452)	(0.315)
	{0.471}	{0.171}	{0.524}	{0.685}	{0.643}	{0.421}	{0.494}	{0.082}	{0.746}	{0.929}	{0.761}	{0.050}	{0.590}	{0.983}	{0.599}	{0.367}
All Controls	-1.701*	-0.596	-1.256**	-0.710	-0.908	-1.180**	-0.965	-0.320*	-0.189	-1.058**	-0.849	0.293	-0.677**	-0.924**	-1.355***	-0.683*
	(0.952)	(0.653)	(0.622)	(0.639)	(0.602)	(0.582)	(0.629)	(0.183)	(0.365)	(0.488)	(0.676)	(0.264)	(0.281)	(0.464)	(0.520)	(0.361)
	{0.611}	{0.219}	{0.541}	{0.748}	{0.814}	{0.625}	{0.821}	{0.096}	{0.648}	{0.903}	{0.842}	{0.128}	{0.502}	{0.860}	{0.629}	{0.286}
Demographic Controls	-1.141	-0.361	-0.996	-0.440	-0.417	-1.013*	-0.619	-0.263*	-0.043	-0.707	-0.630	0.328	-0.494	-0.574	-0.990	-0.488
	(1.418)	(0.941)	(0.825)	(0.738)	(1.177)	(0.599)	(0.502)	(0.154)	(0.439)	(0.851)	(0.468)	(0.264)	(0.350)	(0.567)	(0.951)	(0.493)
	{0.957}	{0.540}	{0.861}	{0.971}	{0.838}	{0.823}	{0.849}	{0.291}	{0.573}	{0.712}	{0.866}	{0.103}	{0.498}	{0.717}	{0.973}	{0.231}
No Controls	-1.141	-0.261	-1.060	-0.437	-0.415	-0.954	-0.545	-0.309*	-0.024	-0.694	-0.616	0.326	-0.490	-0.623	-1.029	-0.440
	(1.272)	(0.926)	(0.784)	(0.711)	(1.056)	(0.650)	(0.524)	(0.161)	(0.425)	(0.896)	(0.437)	(0.267)	(0.305)	(0.520)	(0.840)	(0.449)
	{0.946}	{0.440}	{0.819}	{0.992}	{0.911}	{0.670}	{0.895}	{0.248}	{0.662}	{0.736}	{0.970}	{0.039}	{0.575}	{0.809}	{0.983}	{0.237}
$100,000 Cap	-1.525*	-0.435	-1.252**	-0.641	-0.757	-1.078**	-0.800	-0.353*	-0.131	-0.952*	-0.778	0.301	-0.624**	-0.884*	-1.300***	-0.586**
	(0.806)	(0.731)	(0.634)	(0.760)	(0.621)	(0.482)	(0.555)	(0.185)	(0.336)	(0.491)	(0.752)	(0.245)	(0.265)	(0.519)	(0.482)	(0.299)
	{0.499}	{0.131}	{0.533}	{0.697}	{0.678}	{0.455}	{0.542}	{0.101}	{0.747}	{0.929}	{0.751}	{0.056}	{0.643}	{0.983}	{0.571}	{0.342}
$20,000 Cap	-1.447	-0.432	-1.249*	-0.640	-0.765	-1.078**	-0.788	-0.353**	-0.130	-0.949*	-0.778	0.302	-0.624**	-0.882*	-1.297***	-0.586*
	(0.885)	(0.675)	(0.715)	(0.625)	(0.580)	(0.461)	(0.576)	(0.176)	(0.379)	(0.494)	(0.717)	(0.261)	(0.269)	(0.519)	(0.488)	(0.327)
	{0.537}	{0.139}	{0.525}	{0.695}	{0.680}	{0.418}	{0.525}	{0.057}	{0.750}	{0.921}	{0.748}	{0.090}	{0.621}	{0.986}	{0.561}	{0.395}
Observations	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124
Control Mean ($)	18,784	1,234	1,323	652	6,626	621	2,123	82	365	1,738	542	74	401	1,050	1,442	509

Note: interactive fixed effects approach of Liu et al. (2024); coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; units with less than 5 untreated observations are dropped from the sample. Standard errors clustered by district in parentheses. Pretrend F-tests are in curly braces.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

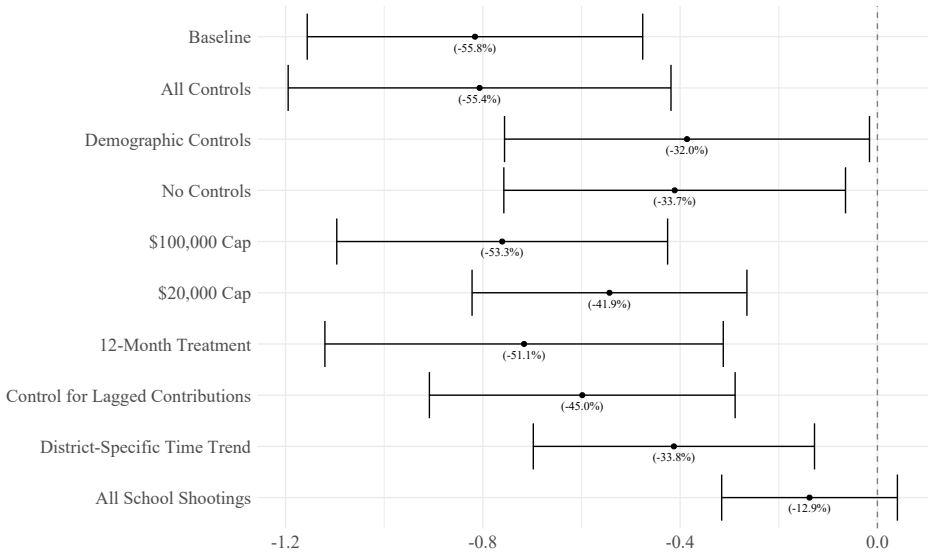
Table D18: Effect of Fatal School Shootings in Competitive Districts on Contributions to Democrats, 2000–2024. Interactive Fixed Effects Model.

	All Corporate	Agriculture	Construction	Defense	Finance, Ins. & Real Estate	Food & Beverage	Health	Hospitality & Tourism	Manuf.	Nonrenewable Energy	Pharma & Health	Renewable Energy	Retail	Tech & Comms	Transport	Vice
Baseline	-0.207	-0.829	0.070	0.487	0.545	0.527	0.284	0.084	0.227	0.941	0.780*	-0.162	0.803***	0.939*	1.072	0.528
	(0.853)	(0.984)	(0.403)	(0.589)	(0.700)	(0.464)	(0.613)	(0.220)	(0.235)	(0.625)	(0.418)	(0.314)	(0.254)	(0.531)	(0.669)	(0.339)
	{0.741}	{0.835}	{0.817}	{0.416}	{0.392}	{0.335}	{0.939}	{0.785}	{0.257}	{0.111}	{0.108}	{0.090}	{0.020}	{0.720}	{0.791}	{0.381}
All Controls	-0.165	-0.716	0.063	0.637	0.498	0.553	0.341	0.108	0.202	1.007	0.787**	-0.159	0.804***	1.049*	1.139	0.558
	(0.879)	(1.075)	(0.524)	(0.569)	(0.680)	(0.543)	(0.650)	(0.189)	(0.238)	(0.674)	(0.341)	(0.291)	(0.236)	(0.554)	(0.771)	(0.376)
	{0.892}	{0.840}	{0.689}	{0.536}	{0.481}	{0.420}	{0.870}	{0.885}	{0.377}	{0.132}	{0.246}	{0.128}	{0.032}	{0.879}	{0.906}	{0.492}
Demographic Controls	-0.730	-0.953	-0.092	0.432	0.077	0.461	-0.008	0.078	0.102	0.782	0.648	-0.183	0.688	0.781	0.904	0.387
	(1.574)	(1.282)	(0.589)	(0.790)	(1.223)	(0.642)	(0.918)	(0.225)	(0.322)	(1.082)	(0.480)	(0.282)	(0.433)	(0.888)	(0.945)	(0.570)
	{0.750}	{0.921}	{0.547}	{0.927}	{0.951}	{0.586}	{0.600}	{0.980}	{0.781}	{0.560}	{0.581}	{0.143}	{0.198}	{0.834}	{0.803}	{0.814}
No Controls	-0.636	-1.003	-0.051	0.339	0.225	0.457	0.020	0.062	0.150	0.773	0.677	-0.181	0.715*	0.742	0.897	0.398
	(1.571)	(1.220)	(0.557)	(0.707)	(1.159)	(0.600)	(0.878)	(0.252)	(0.331)	(0.939)	(0.528)	(0.330)	(0.372)	(0.960)	(0.924)	(0.566)
	{0.844}	{0.932}	{0.647}	{0.811}	{0.815}	{0.586}	{0.783}	{0.913}	{0.650}	{0.491}	{0.474}	{0.182}	{0.108}	{0.979}	{0.920}	{0.664}
$100,000 Cap	-0.210	-0.829	0.070	0.487	0.546	0.527	0.286	0.084	0.227	0.941	0.780**	-0.162	0.803***	0.939	1.072	0.528
	(0.897)	(1.045)	(0.398)	(0.604)	(0.705)	(0.503)	(0.590)	(0.232)	(0.204)	(0.626)	(0.388)	(0.304)	(0.241)	(0.579)	(0.729)	(0.395)
	{0.753}	{0.851}	{0.828}	{0.464}	{0.402}	{0.325}	{0.944}	{0.806}	{0.259}	{0.123}	{0.112}	{0.121}	{0.019}	{0.734}	{0.781}	{0.411}
$20,000 Cap	-0.351	-0.828	0.070	0.487	0.501	0.527	0.301	0.084	0.227	0.938	0.780*	-0.162	0.803***	0.939	1.072	0.527
	(0.781)	(0.960)	(0.454)	(0.569)	(0.726)	(0.507)	(0.580)	(0.223)	(0.217)	(0.599)	(0.404)	(0.296)	(0.232)	(0.587)	(0.806)	(0.379)
	{0.850}	{0.842}	{0.843}	{0.438}	{0.437}	{0.313}	{0.949}	{0.785}	{0.251}	{0.104}	{0.099}	{0.153}	{0.019}	{0.738}	{0.790}	{0.419}
Observations	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124	8,124
Control Mean ($)	11,036	845	381	516	4,115	163	2,022	51	184	541	395	44	174	737	546	324

Note: interactive fixed effects approach of Liu et al. (2024); coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; units with less than 5 untreated observations are dropped from the sample. Standard errors clustered by district in parentheses. Pretrend F-tests are in curly braces.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

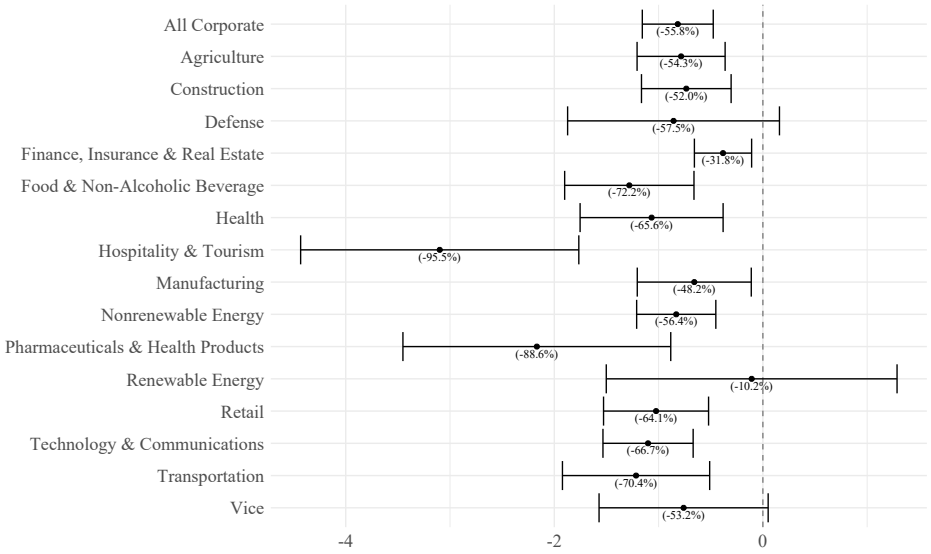
5. Direct Expenditures Only

Figure D33: Fatal School Shootings Reduce Corporate Direct Contributions to Republicans in Competitive Districts Across Specifications, 2000–2024. Static PPML Model.



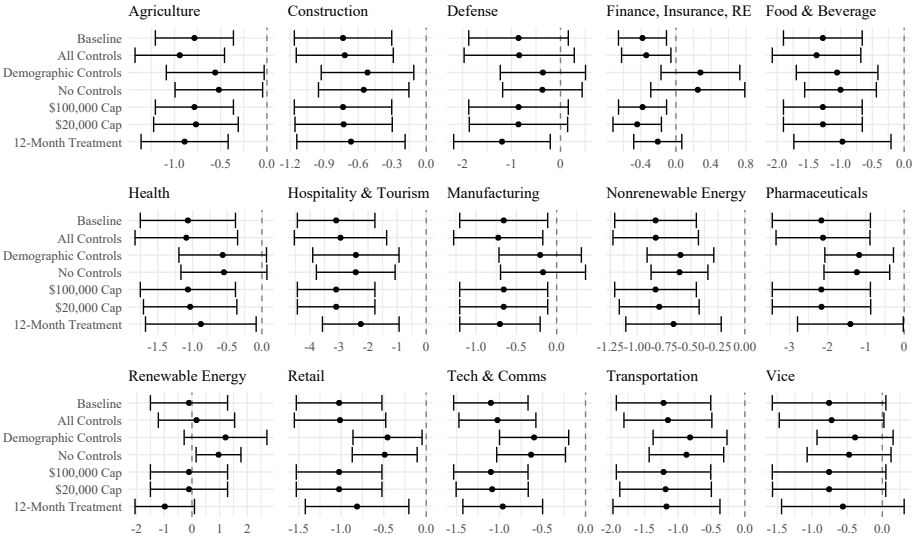
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions in all observations are excluded prior to estimation. When controlling for lagged contributions, the variance-covariance matrix could not be verified as positive semi-definite; interpret with caution. Standard errors are clustered by district.

Figure D34: Fatal School Shootings Reduce Corporate Direct Contributions to Republicans in Competitive Districts Across Sectors, 2000–2024. Static PPML Model.



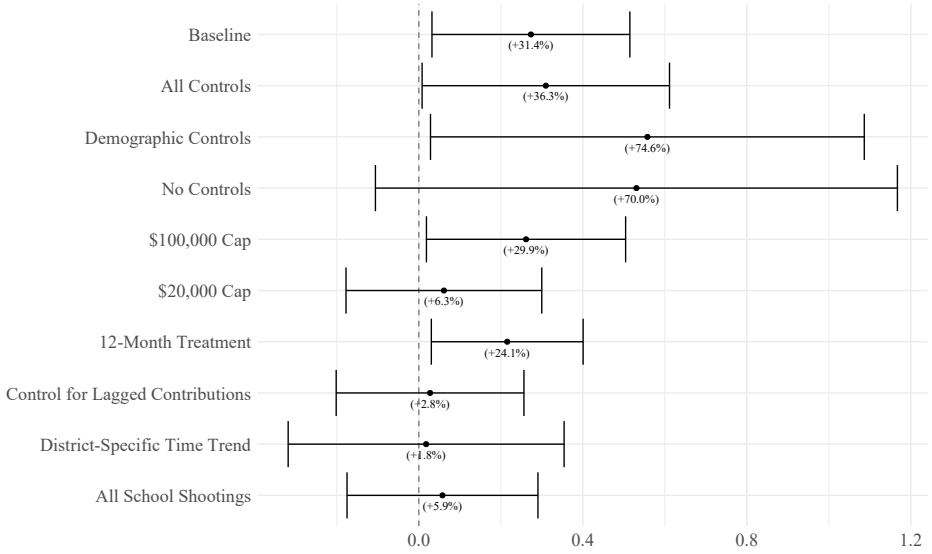
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D35: Fatal School Shootings Reduce Corporate Direct Contributions to Republicans in Competitive Districts Across Sectors and Specifications, 2000–2024. Static PPML Model.



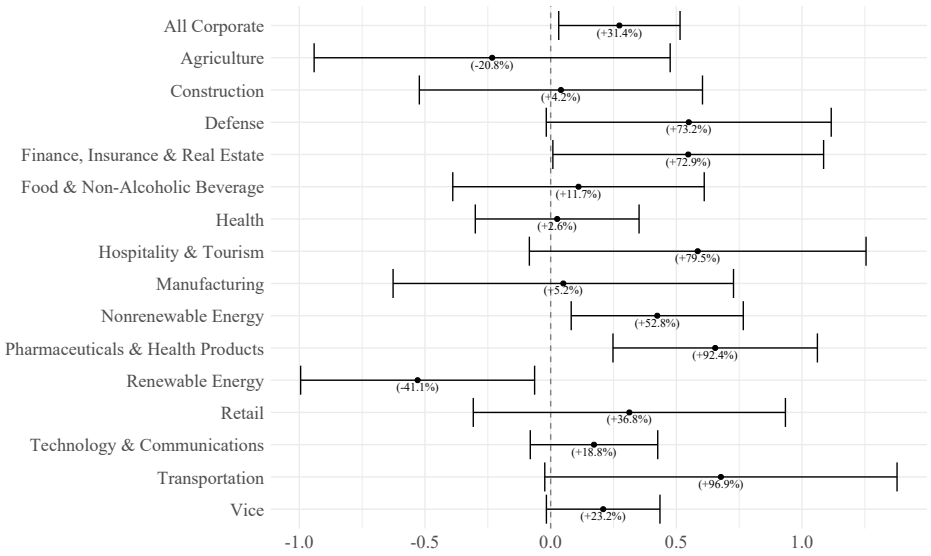
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D36: Fatal School Shootings Don't Impact Corporate Direct Contributions to Democrats in Competitive Districts Across Specifications, 2000–2024. Static PPML Model.



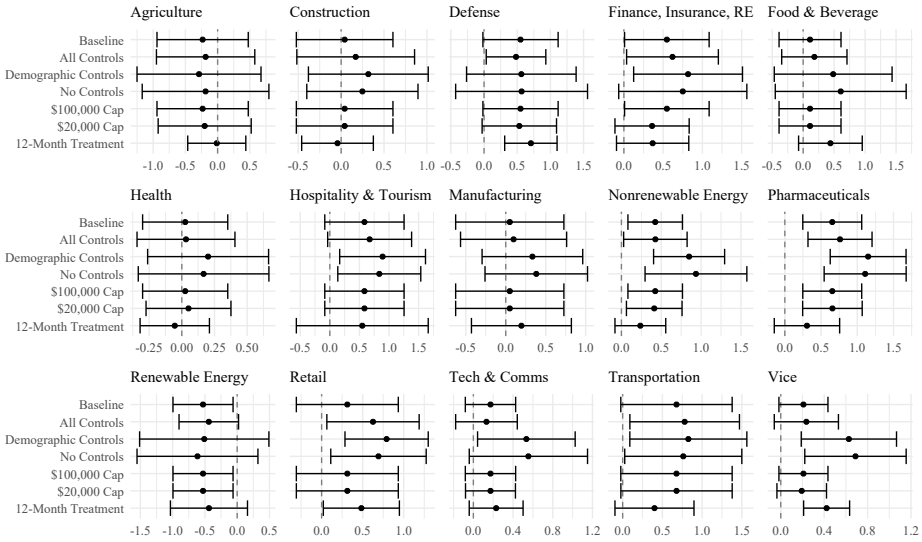
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. When controlling for lagged contributions, the variance-covariance matrix could not be verified as positive semi-definite; interpret with caution. Standard errors are clustered by district.

Figure D37: Fatal School Shootings Don't Impact Corporate Direct Contributions to Democrats in Competitive Districts Across Sectors, 2000–2024. Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

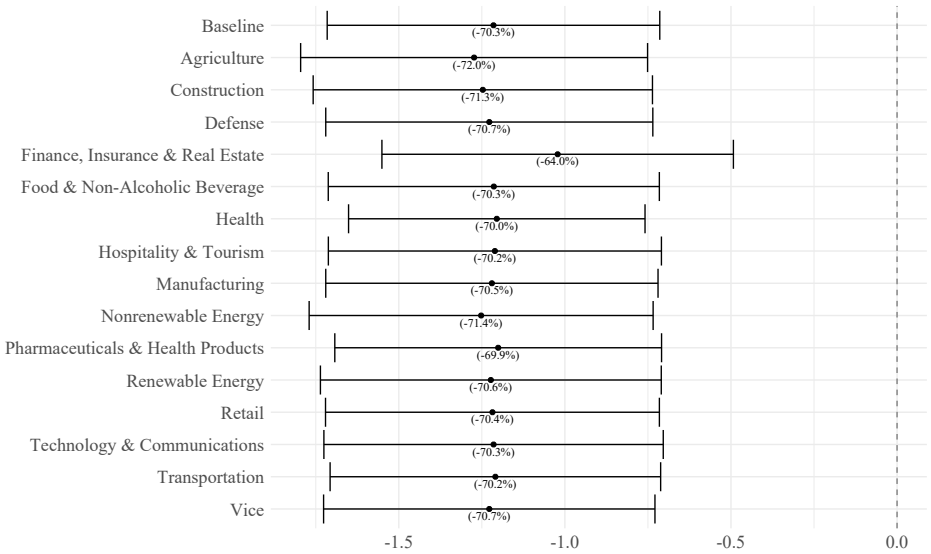
Figure D38: Fatal School Shootings Don't Impact Corporate Direct Contributions to Democrats in Competitive Districts Across Sectors and Specifications, 2000–2024. Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

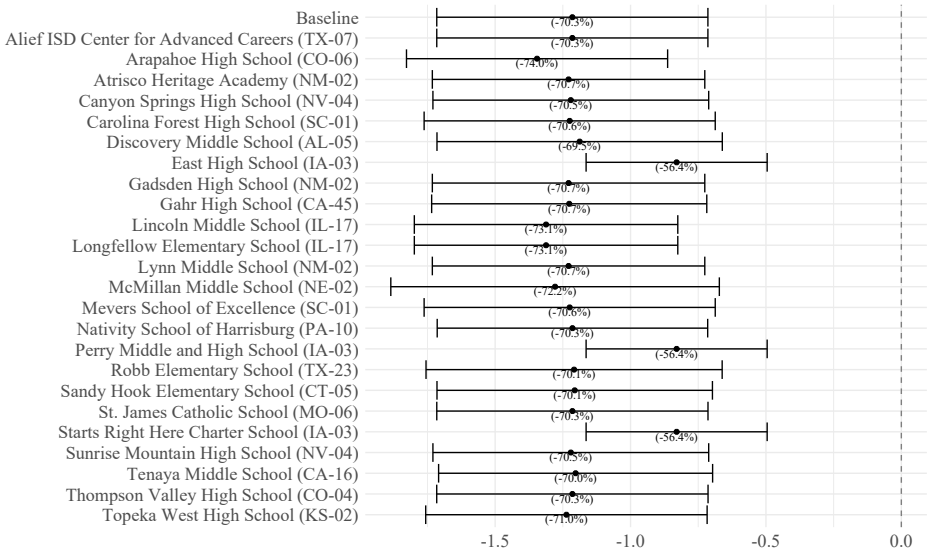
6. Leave-One-Out

Figure D39: Impact of Fatal School Shootings on Contributions to Republicans in Competitive Districts Not Driven by Any Single Sector, 2000–2024. Static PPML Model.



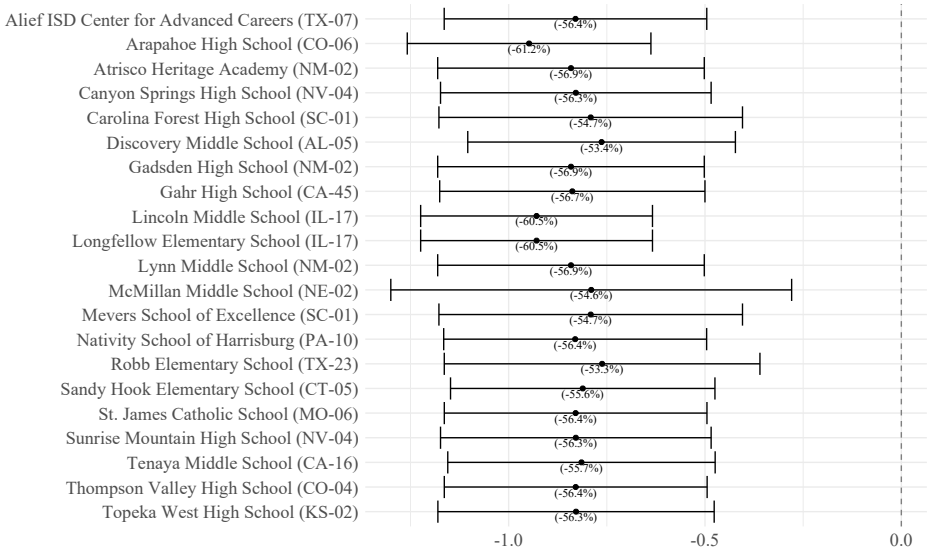
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions. Each coefficient corresponds to the impact of fatal school shootings on corporate contributions to Republicans, from all sectors except the specified sector. Standard errors are clustered by district.

Figure D40: Leave-One-District-Out Analysis Excluding Each District Affected by a Fatal School Shooting, 2000–2024. Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions. Each coefficient corresponds to the impact of fatal school shootings on corporate contributions to Republicans, removing the district corresponding to the specified shooting from the sample. Standard errors are clustered by district.

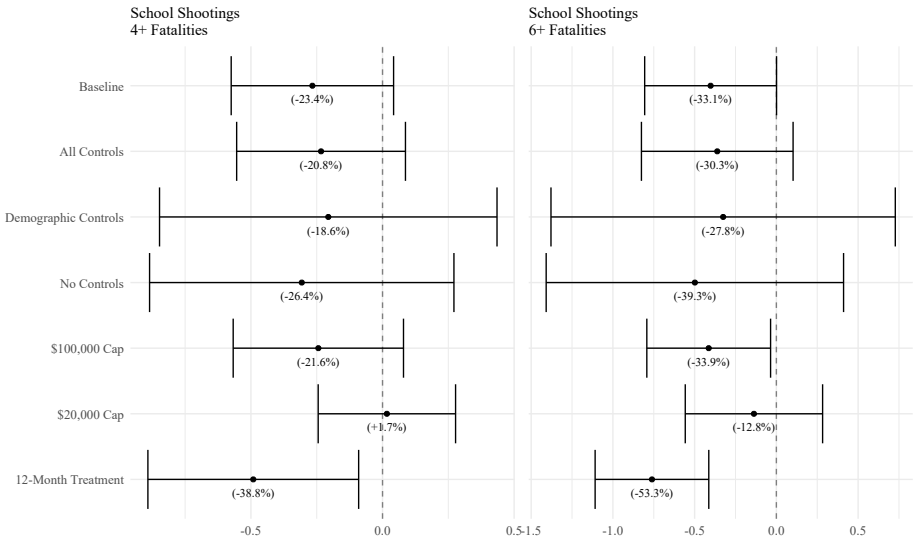
Figure D41: Leave-One-District-Out Analysis Excluding IA-03 and An Additional District, 2000–2024. Static PPML Model.



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions. Each coefficient corresponds to the impact of fatal school shootings on corporate contributions to Republicans, removing IA-03 and the district corresponding to the specified shooting from the sample. Standard errors are clustered by district.

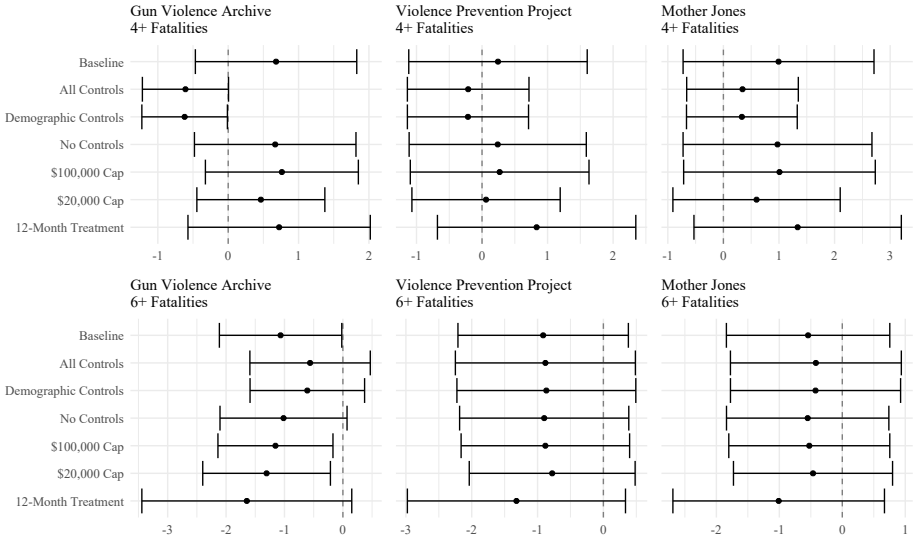
7. Alternative Shooting Types

Figure D42: High-Fatality School Shootings Do Not Affect Corporate Contributions to Republicans Across Specifications, 2000–2024. Static PPML Model.



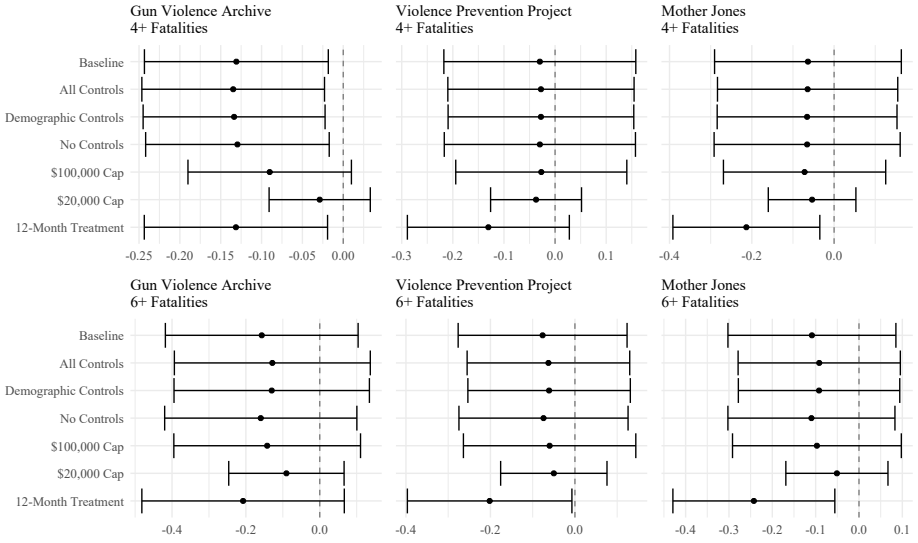
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D43: Only High-Fatality Mass Shootings Reduce Corporate Contributions to Republicans in Safe Democratic (Over 5%) Districts Across Specifications and Shooting Databases, 2000–2024. Static PPML Model.



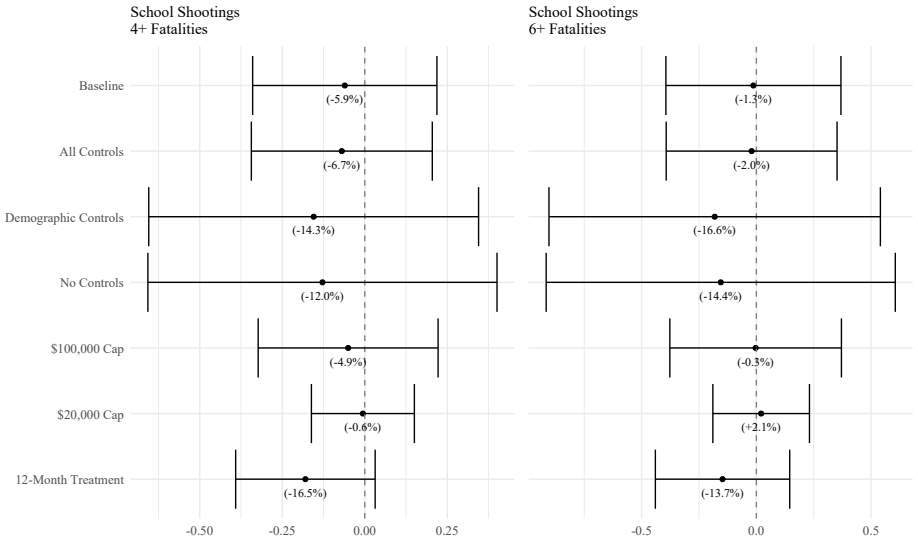
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D44: Mass Shootings Do Not Affect Corporate Contributions to Republicans in Safe Republican (Over 5%) Districts Across Specifications and Shooting Databases, 2000–2024. Static PPML Model.



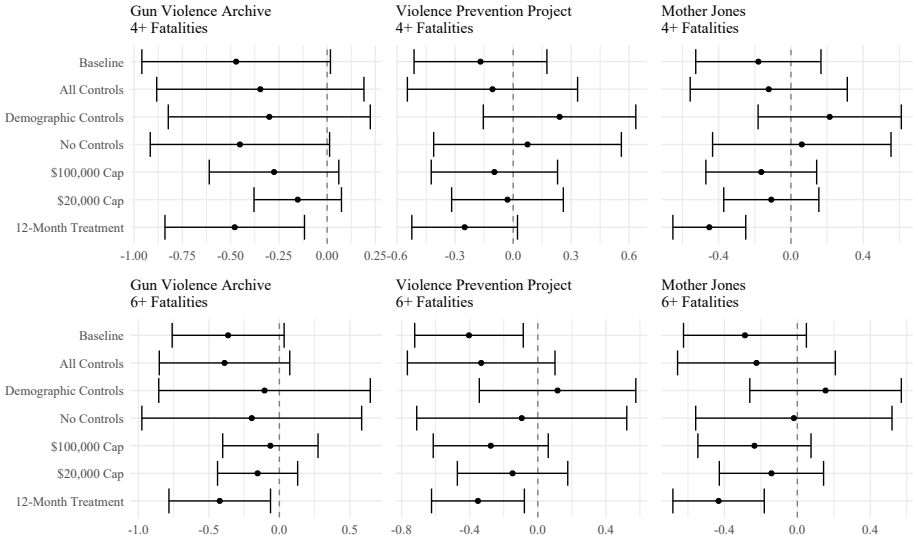
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D45: High-Fatality School Shootings Do Not Affect Corporate Contributions to Democrats Across Specifications, 2000–2024. Static PPML Model.



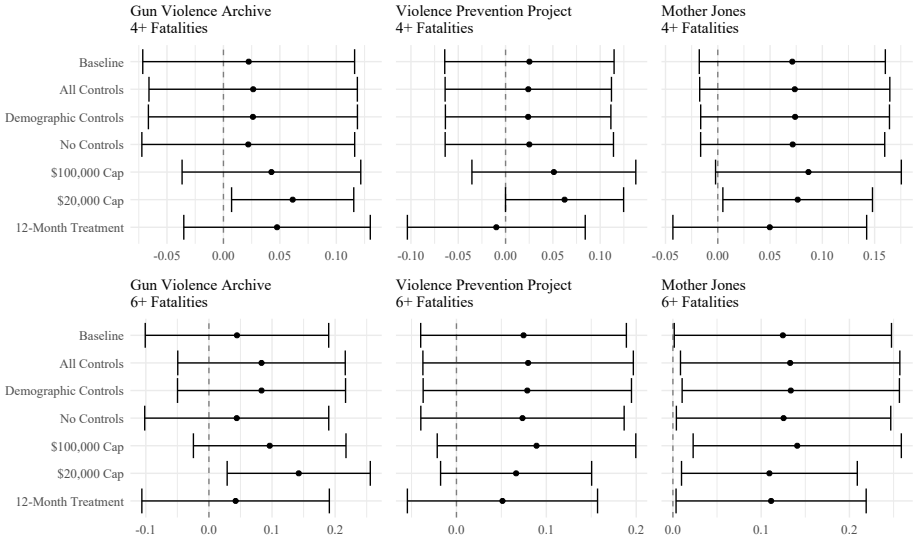
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D46: Mass Shootings Do Not Affect Corporate Contributions to Democrats in Competitive Districts Across Specifications and Shooting Databases, 2000–2024. Static PPML Model.



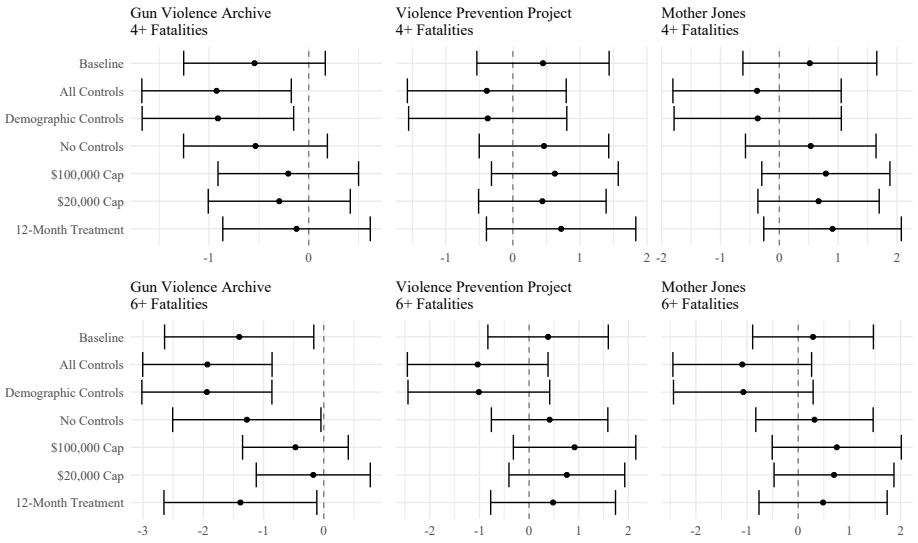
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D47: Mass Shootings Do Not Affect Corporate Contributions to Democrats in Safe Democratic (Over 5%) Districts Across Specifications and Shooting Databases, 2000–2024. Static PPML Model.



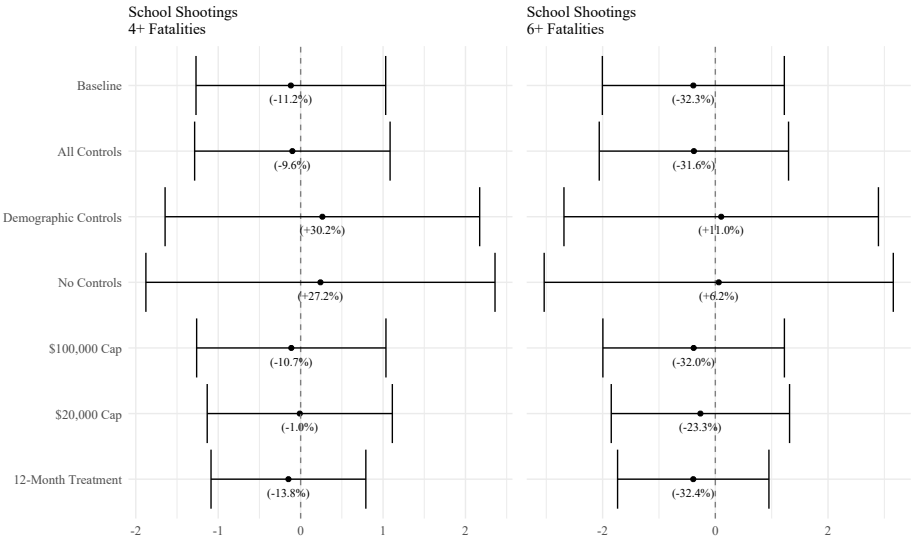
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D48: Mass Shootings Do Not Affect Corporate Contributions to Democrats in Safe Republican (Over 5%) Districts Across Specifications and Shooting Databases, 2000–2024. Static PPML Model.



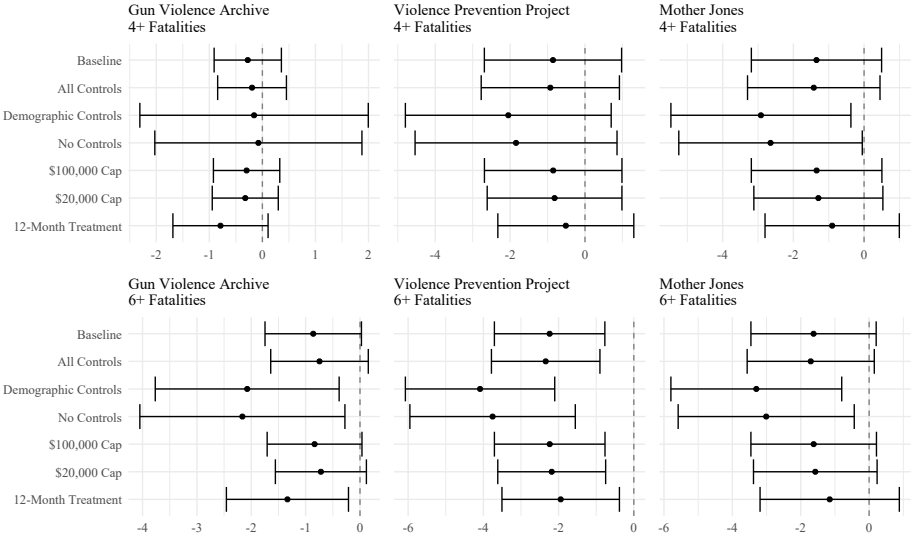
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; districts and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D49: High-Fatality School Shootings Do Not Affect Corporate Contributions to Republicans Across Specifications, 2000–2024. Static Log-Linear Model.



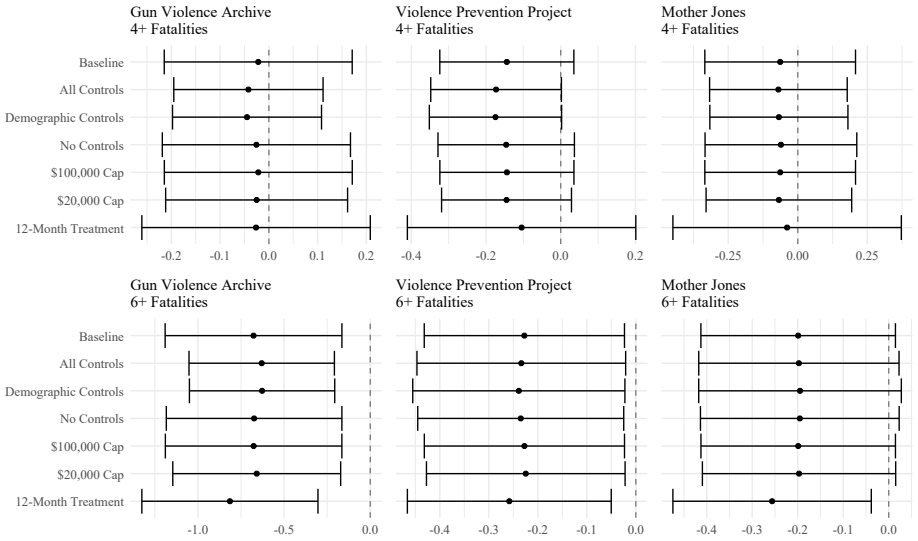
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D50: Only High-Fatality Mass Shootings Reduce Corporate Contributions to Republicans in Competitive Districts Across Specifications and Shooting Databases, 2000–2024. Static Log-Linear Model.



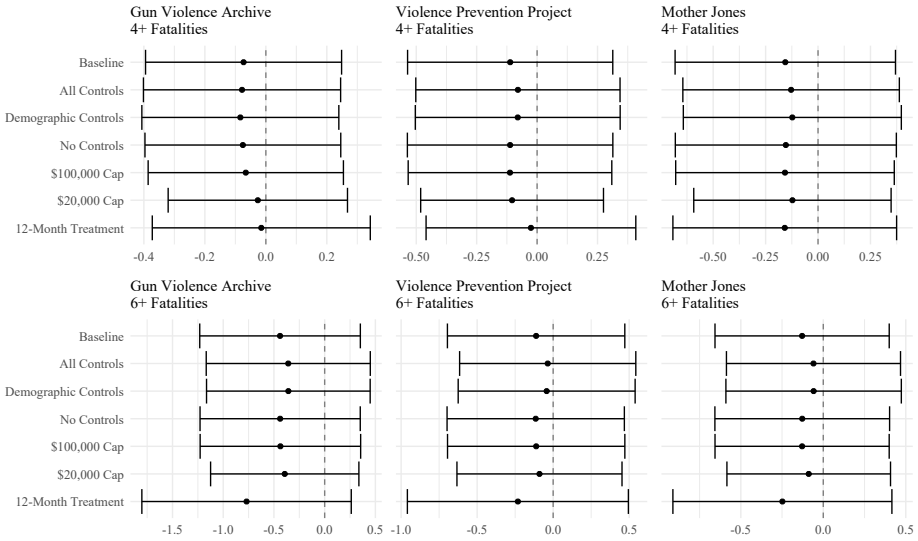
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D51: Only High-Fatality Mass Shootings Reduce Corporate Contributions to Republicans in Safe Democratic (Over 5%) Districts Across Specifications and Shooting Databases, 2000–2024. Static Log-Linear Model.



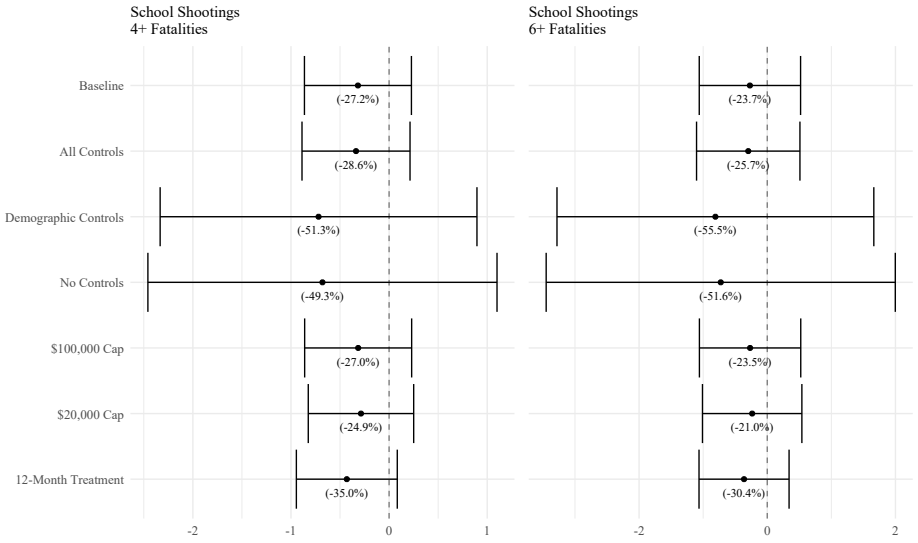
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D52: Mass Shootings Do Not Affect Corporate Contributions to Republicans in Safe Republican (Over 5%) Districts Across Specifications and Shooting Databases, 2000–2024. Static Log-Linear Model.



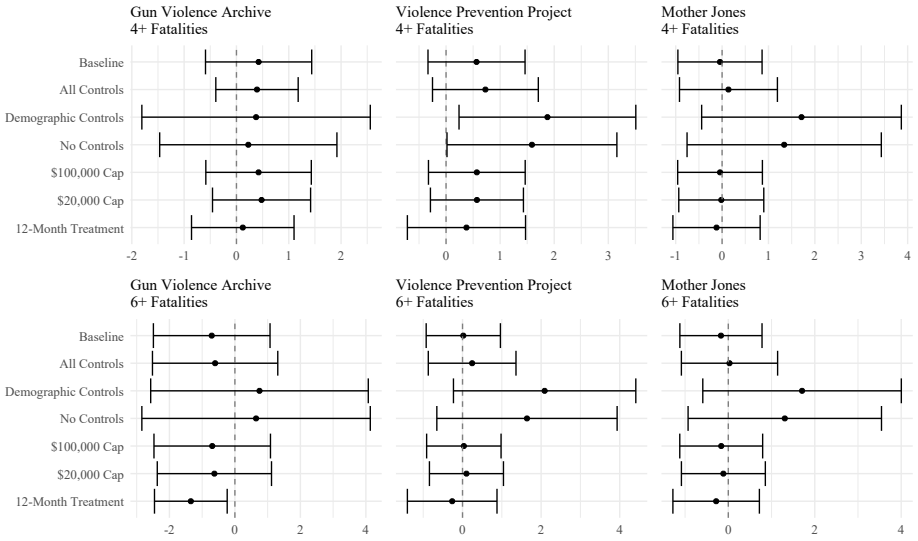
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D53: High-Fatality School Shootings Do Not Affect Corporate Contributions to Democrats Across Specifications, 2000–2024. Static Log-Linear Model.



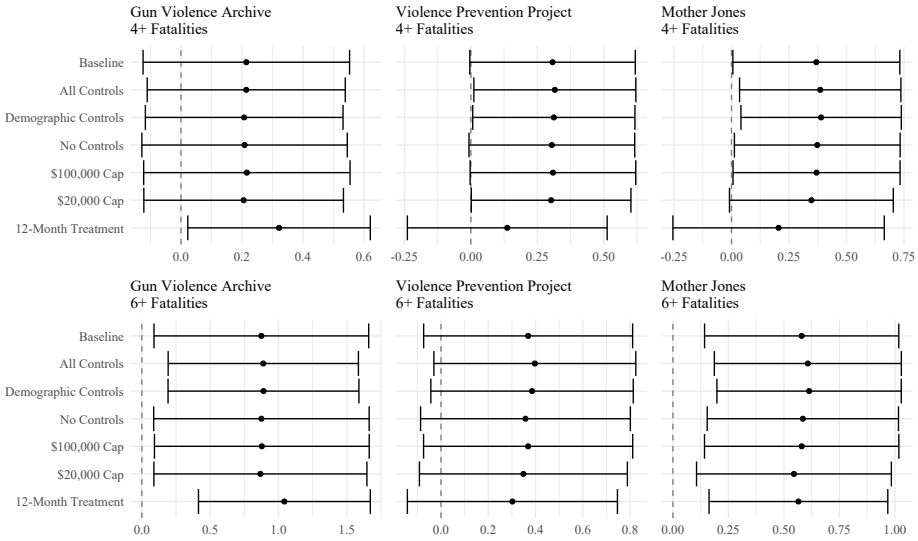
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D54: Mass Shootings Do Not Affect Corporate Contributions to Democrats in Competitive Districts Across Specifications and Shooting Databases, 2000–2024. Static Log-Linear Model.



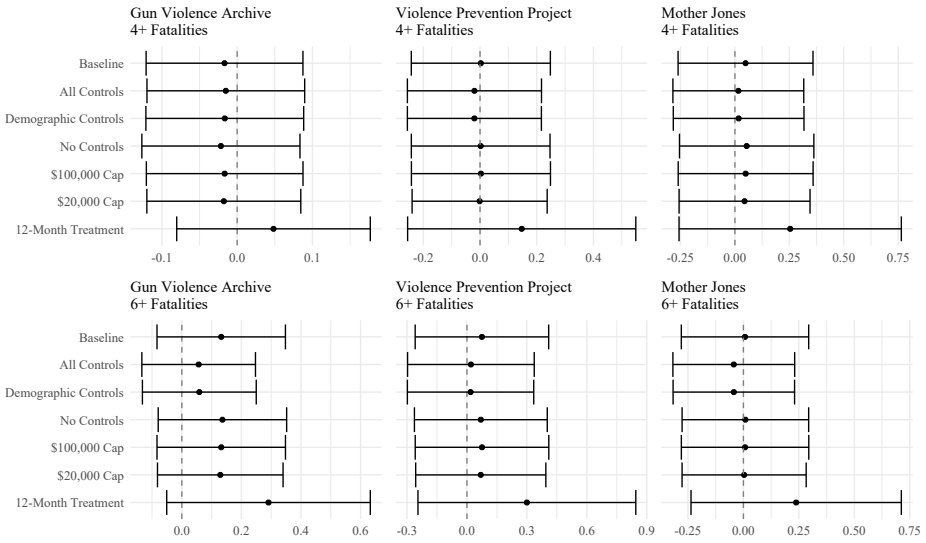
Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D55: Mass Shootings Do Not Affect Corporate Contributions to Democrats in Safe Democratic (Over 5%) Districts Across Specifications and Shooting Databases, 2000–2024. Static Log-Linear Model.



Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

Figure D56: Mass Shootings Do Not Affect Corporate Contributions to Democrats in Safe Republican (Over 5%) Districts Across Specifications and Shooting Databases, 2000–2024. Static Log-Linear Model.



Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by district.

8. Geographic Spillover

A key assumption underlying all difference-in-differences models is the stable-unit treatment value assumption (SUTVA). In this context, SUTVA implies that fatal school shootings do not impact campaign contributions to candidates in neighboring congressional districts. To test whether spillover occurs, we compute the distances between all fatal school shootings in our datasets and the centers of neighboring districts. We use three definitions of district center: population centroid, geographic centroid, and point on surface.

Population centroids are taken directly from Geocorr (Missouri Census Data Center 2000, 2014, 2018, 2022). Geographic centroids are calculated using congressional district shapefiles and the `st_centroid` function from the `sf` package in R (Pebesma 2018). Since district centroids may lie outside district boundaries for nonconvex districts, we also calculate points guaranteed to be within the district using the `st_point_on_surface` function from the `sf` package in R, which returns a point guaranteed to lie in the interior of the district (Pebesma 2018). Shapefiles for the 101st through 114th Congress are sourced from Lewis et al. (2017), and shapefiles for the 115th through 119th Congress are sourced from Walker (2025).

$$E(\text{Contrib}_{dm}|\cdot) = \exp(\gamma_d + \lambda_m + \delta \cdot \text{Near}_{dm} + x'_{dm} \cdot \beta) \tag{D2}$$

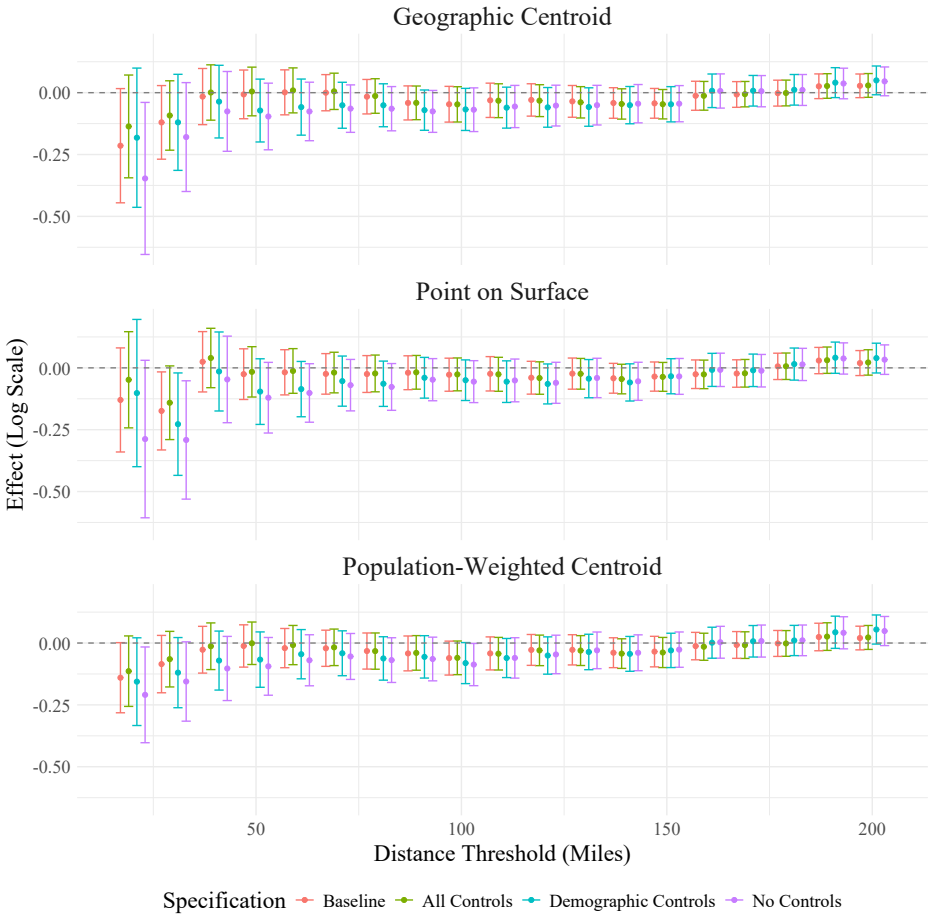
We then compute the distance between all fatal school shootings in the sample period and the three district centers. In each analysis of Figure D57, a district-month is defined as treated

if a fatal school shooting occurred within the past 24 months outside the district boundaries but within a distance less than the threshold to the district center. Districts that experienced a fatal school shooting within their own borders in the past 24 months are filtered out of the sample. Treatment effects are computed with this updated treatment definition, but all other features of our model remain the same. The outcome is total corporate contributions to Republican House candidates in district d in month m, estimated via Equation D2, where Near_{dm} is the treatment indicator defined above. Thus, Figure D57 compares district-months near recent fatal school shootings to district-months far from recent fatal school shootings, excluding district-months that recently experienced fatal school shootings themselves.

Figure D58 shows the result of a similar analysis focused on competitive districts. The data are prepared and analyzed analogously to Figure D57, but the sample is restricted to district-months in which the margin of the most recent prior election was under 5%. This restriction only applies to the district-months included in the regression: any fatal school shooting, regardless of whether it occurs in a competitive or non-competitive district, can trigger treatment in a nearby competitive district. To mirror the competitiveness-at-time-of-shooting requirement, district-months count as treated only if the district was competitive at the time of the fatal school shooting in the nearby district. Thus, Figure D58 compares competitive district-months near recent fatal school shootings to competitive district-months far from recent fatal school shootings, excluding competitive district-months that recently experienced fatal school shootings themselves.

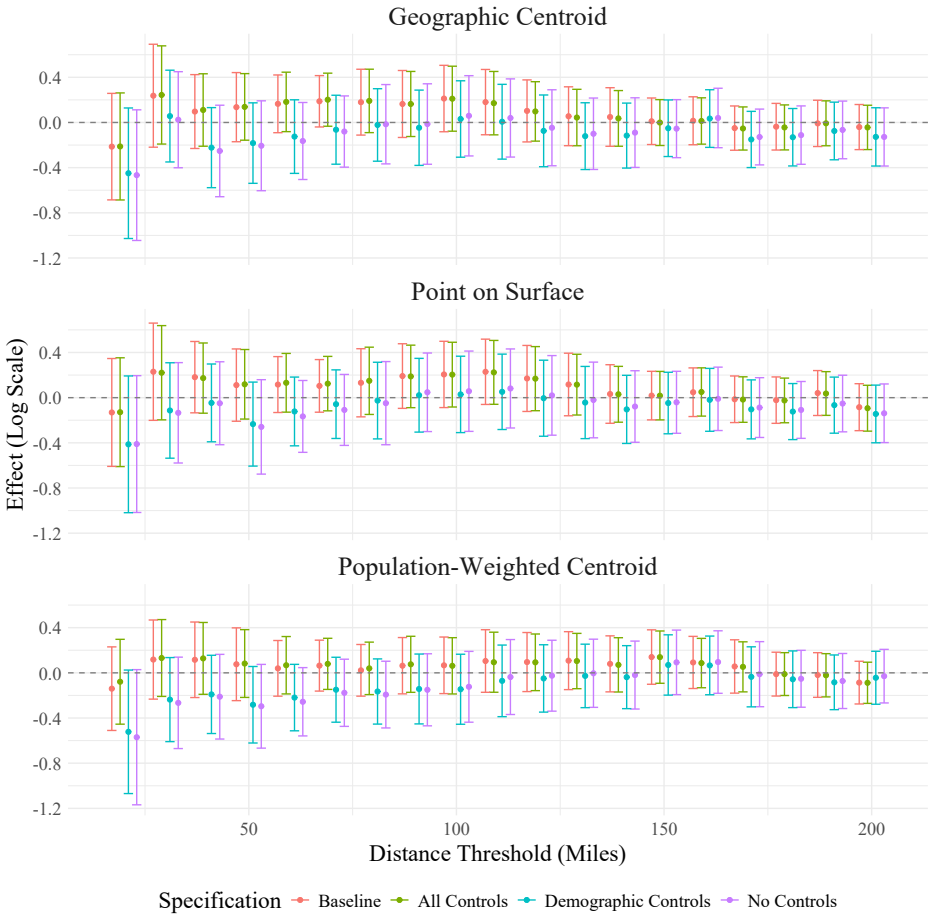
The results suggest that fatal school shootings do not have a substantial impact on nearby districts. In all results employing the 20-mile distance threshold, the estimated effect of fatal school shootings on nearby districts is negative. This suggests that if anything, fatal school shootings may cause slight decreases in corporate contributions to Republican House candidates in nearby districts, suggesting that nearby districts may be partially treated. To the extent that nearby districts are partially treated, our main estimates represent a lower bound on the maghnitude of the true effect.

Figure D57: Spillover Analysis: All Districts



Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; districts and months with zero contributions in all observations are excluded prior to estimation. Standard errors are clustered by district.

Figure D58: Spillover Analysis: Competitive Districts

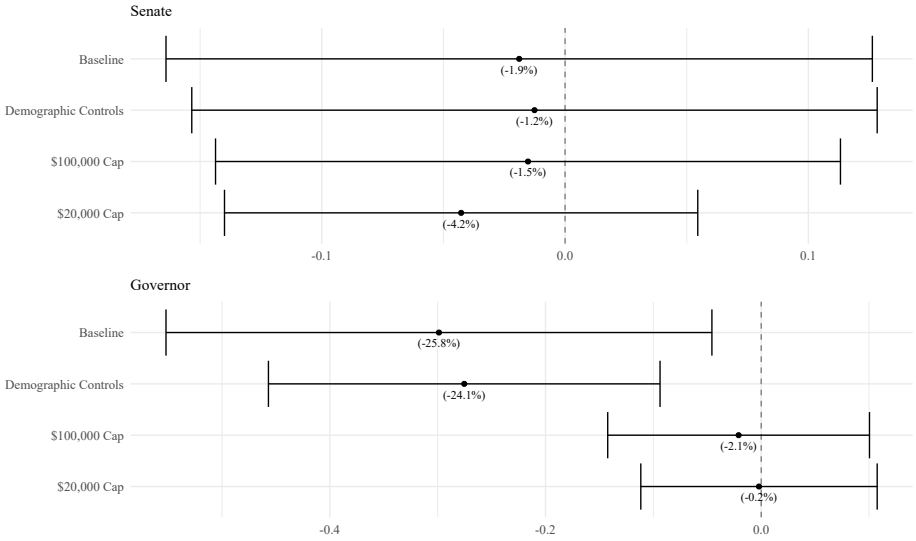


Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; districts and months with zero contributions in all observations are excluded prior to estimation. Standard errors are clustered by district.

9. Spillover to Statewide Elections

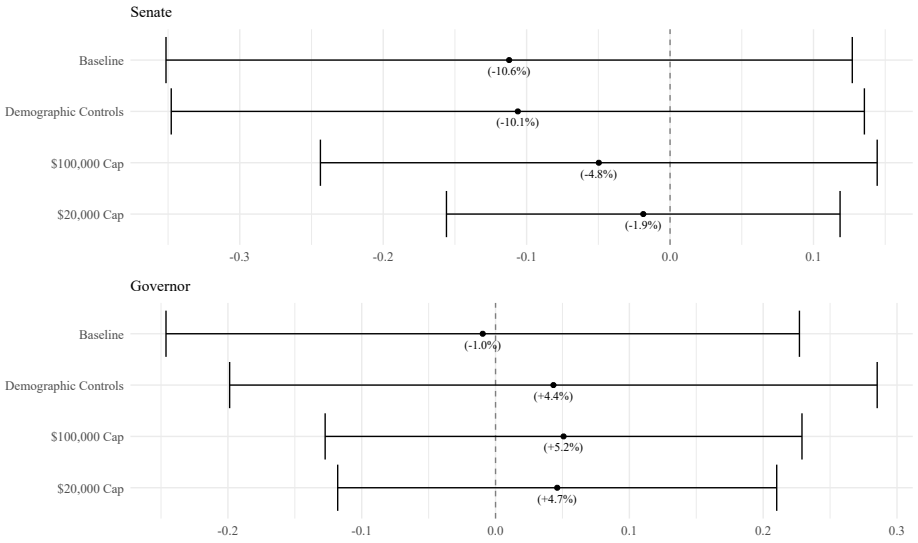
To assess whether the contribution response extends beyond House races to statewide offices, we estimate the impact of fatal school shootings on corporate contributions to Republican and Democratic candidates for U.S. Senate and Governor. State-level corporate contributions are also from OpenSecrets (OpenSecrets 2025). We construct a state-month panel running from December 1999 through November 2024, linking fatal school shootings to contributions at the state level using the same treatment definition as the main analysis: a state is treated for 24 months following any fatal school shooting occurring within its borders. Unlike the main analysis, we do not restrict the sample to competitive races, as applying this would leave too few observations for meaningful inference. We estimate the same static PPML and log-linear specifications as in the main analysis, with state and month fixed effects and standard errors clustered by state. We did not use election-related controls in this analysis, as the timing of Senate and gubernatorial elections varies by state.

Figure D59: Impact of Fatal School Shootings on Corporate Contributions to Republicans Seeking Statewide Office, 2000–2024. Static PPML Model.



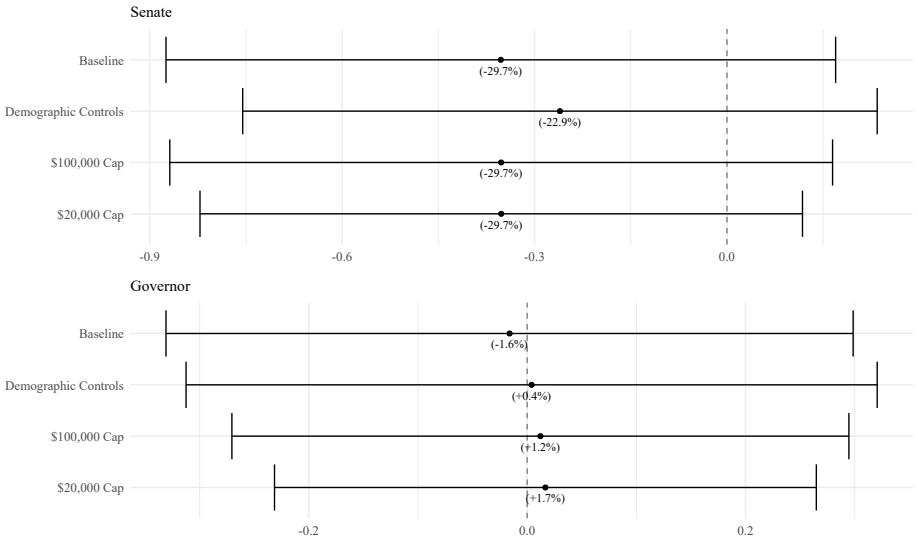
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; states and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by state.

Figure D60: Impact of Fatal School Shootings on Corporate Contributions to Democrats Seeking Statewide Office, 2000–2024. Static PPML Model.



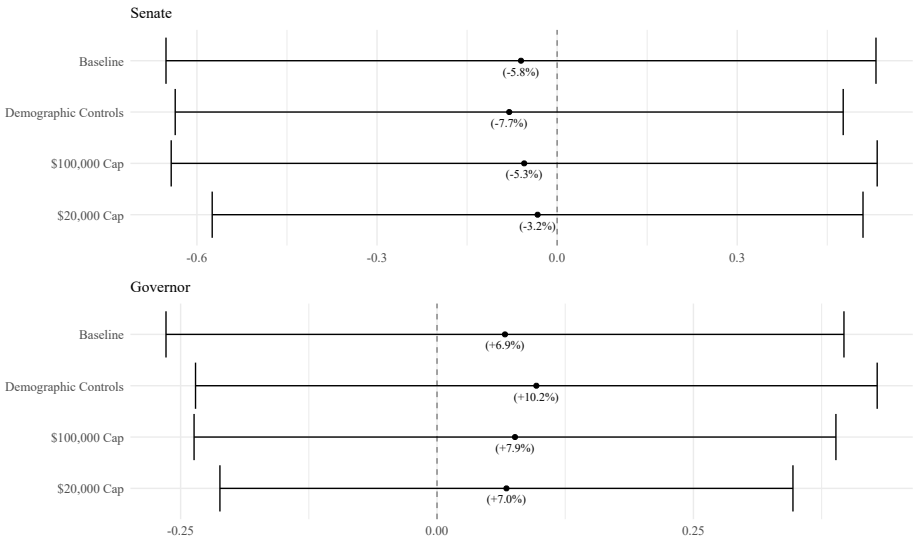
Note: static pseudo-Poisson maximum likelihood model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal; states and months with zero contributions across all observations are excluded prior to estimation. Standard errors are clustered by state.

Figure D61: Impact of Fatal School Shootings on Corporate Contributions to Republicans Seeking Statewide Office, 2000–2024. Static Log-Linear Model.



Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by state.

Figure D62: Impact of Fatal School Shootings on Corporate Contributions to Democrats Seeking Statewide Office, 2000–2024. Static Log-Linear Model.



Note: static log-linear OLS model with two-way fixed effects; coefficients are in log scale; exponentiating them yields multiplicative effects on contributions; dollar amounts are nominal. Standard errors are clustered by state.